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SCENIC BEAUTY ESTIMATION MODELS
for
SOUTHWEST FOREST ECOSYSTEM
PLANNING and MANAGEMENT

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Scenic Beauty Estimation Models for Southwest Forest Ecosystem Planning and Management

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between
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The objectives of this agreement were to:

1. Select and test a suite of forest ecosystem data visualization systems for representing the effects of alternative forest management actions on mid-range and panoramic forest vistas;

2. Develop and test statistically-based vista scenic beauty estimation assessment methods and prediction models for restricted (mid-range) and panoramic views characteristic of forest landscapes in visually sensitive areas of the Dixie National Forest; and

3. Extend existing statistically-based, near-view scenic beauty estimation assessment methods and models for application to high elevation spruce-fir forest types on the Dixie National Forest.

This final report consists of four papers. Those papers and the objectives they address are:

1. Data visualization for forest health management decision support, by Terry C. Daniel, Michael J. Meitner, and Brian Orland, which appeared in *Resource Technology 1997: Beijing International Symposium Proceedings*, China Forestry Publishing House, Beijing, pages 239-249 (objective 1);

2. Vista scenic beauty estimation model: an application of integrating neural net and geographic information systems, a Master's thesis by Yu-Lan Yuan (objective 2);

3. Vista scenic beauty estimation modeling: a GIS approach, by Michael J. Meitner and Terry C. Daniel, which appeared in *Proceedings of 1997 ESRI User Conference,* Redlands, CA, July 1997, published at http://www.esri.com/library/userconf/ proc97/ abstract/A202 (objective 2); and

4. A method for assessing near view scenic beauty models: a comparison of neural networks and multiple linear regression, a Master's thesis by Miles M. Flynn (objective 3).

DATA VISUALIZATION FOR FOREST HEALTH MANAGEMENT DECISION SUPPORT

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ABSTRACT

Forest health management decisions are often based on long range projections of future forest conditions, including the effects of health affecting agents. These conditions and effects can be complex and difficult for those not trained or experienced in forest health management to understand. Modern computer-based environmental data visualization systems have been found to be of great assistance in this context. Forest health experts can use high-speed, analytic visualizations to interactively explore the visual characteristics of forests and forest health changes at stand and landscape scales. Interdisciplinary forest management teams can more effectively come to a mutual understanding of expected changes in forest conditions, and of the effects of forest health agents on those conditions. Photographically realistic visualizations can help concerned public audiences to better understand and appreciate the motivations and intentions of proposed forest health management actions. These and other potential uses of computer data visualizations in the context of forest health management are reviewed and evaluated using examples from recently completed and ongoing projects.

INTRODUCTION

Computer data visualization technology is increasingly available, and is increasingly used to support environmental planning and management (e.g., Bishop, 1992; Cullati, et al, 1992; Malm ,et al, 1981; Orland, 1992), including applications designed specifically for support of forest health planning and management (e.g., Baker & Rabin, 1988; Daniel, et al 1990; 1992; Lynch, 1992; Lynch et al, 1994; Orland, et al, 1992). Modern data visualization systems translate quantitative, data projections of future (or desired) forest conditions into concrete visual representations. Unlike traditional "artist's conceptions" or "illustrations," data visualization emphasizes systematic, traceable links between forest bio-physical data and the features presented in the visualization (Daniel, 1992; Orland, 1988; 1993).

A diverse array of computer graphic tools are available to translate complex spatial data into visual landscape representations. Visualization products vary enormously in fidelity and resolution, with some achieving a very high level of apparent realism. Visualizations, whether crude wire-frames or high-resolution, full color animations that approach "virtual reality," are almost uniformly assumed to be helpful in giving forest managers and/or concerned publics a fuller and more accurate understanding of forest conditions, which are otherwise only represented as abstract data.

However sophisticated, and whatever the technical properties achieved, the utility of data visualizations depends importantly on the extent to which they achieve the intended understandings or reactions from the targeted audience (whether expert analysts or general publics). If the intention of a visualization is to accurately show the location and extent of some forest feature in the landscape (such as the area of impact from an insect or pathogen outbreak), it will be successful to the extent that it consistently helps users accurately to identify and locate the designated areas in the forest landscape represented. For that purpose, a simple schematic map be a sufficient, or even the best "visualization." If, on the other hand, the intention is to determine how the impacted areas will affect public viewers' aesthetic appreciation of a critical view in which the impact occurs, a simple map be an entirely insufficient and inappropriate representation. In fact research suggests that such situations require a very high level of realism in the representation of the forest landscape (Daniel & Meitner, 1997). In general, the utility of an environmental visualization will be indicated by the extent to which it provides a representation that is sufficient to produce perceptions, evaluations, or reactions that closely parallel responses the same observers would make when directly observing the forest areas and conditions depicted.

A number of data visualization techniques have been developed and applied to support forest health planning and management (e.g., Baker & Rabin, 1988; Daniel, et al 1997; Heasley, 1992; Orland, 1993). These systems differ in intent and in technical approach. Some (e.g., Orland, 1994) were primarily designed and intended to support trained analysts in evaluating both visual and other effects of alternative forest management plans. These systems typically provide only relatively abstract visualizations of forest sites, emphasizing very close and rapid connections with the underlying bio-physical data sets (often derived from forest growth models). Visualizations intended for general public audiences have emphasized more realistic representations, typically at the expense of close and efficient connections to underlying forest data (e.g., Baker & Rabin, 1988; Daniel, et al, 199X; Orland, 199X).

Two recently completed studies investigating the effects of the "level of abstraction/realism" in forest data visualizations are described below. In the first study audiences representative of general publics provided perceptual judgments for a sample of forest areas based on observing either abstract or more realistic representations of those sites. The second study compared forest health experts' professional evaluations based on high resolution visualizations of a forest stand that varied systematically in forest health relevant parameters. For half of the expert judges the forest scene was shown in *true color* and for the other half the visualizations were modified by the introduction of *false color* designed to enhance the visual conspicuity of the relevant stand parameters. This same set of forest visualizations (in true and in false color) were also presented to audiences representative of the general public for perceptual/aesthetic evaluations. The question of interest in both studies was how the visualization techniques represented affected forest health related judgments of the sites depicted for the targeted audiences/purposes.

Study 1 Public Judgments of Analytic Versus Realistic Forest Visualizations

Perceptions of abstract and more realistic visualizations of forest sites were compared in this study. Separate observer panels made perceptual judgments of either *perceived scenic beauty* or of *recreational quality* (for overnight camping) for a sample of forest sites based on either abstract (trees represented as 3-D solid objects) or more realistic (trees and ground surface video textured) representations. Internal reliability and cross-representational agreement in perceptual judgments were assessed.

Procedures-Visualizations for this study were created by SmartForest, a forest landscape visualization software package designed to represent changing forest site characteristics rapidly (Orland, 1994). In SmartForest stand-level data is distributed statistically on the landscape to locate tree symbols scaled to the size of tree records which together offer a schematic representation of tree density, size, condition and homogeneity of stand composition in correct visual perspective. The program features are described in detail via the World Wide Web at *http://www.imlab.uiuc.edu/SF/SF.html*.

SmartForest is an interactive, graphically-oriented forest environment, developed at the Imaging Systems Laboratory, University of Illinois in collaboration with the USDA Forest Service. The user can view the ground level perspectives within a forest, "walk" between the trees, view large forest areas from user-defined aerial heights and/or classify stands and trees by highlighting them with different user-defined color-codes. SmartForest operates in two different modes: *management mode* and *landscape analysis mode*.

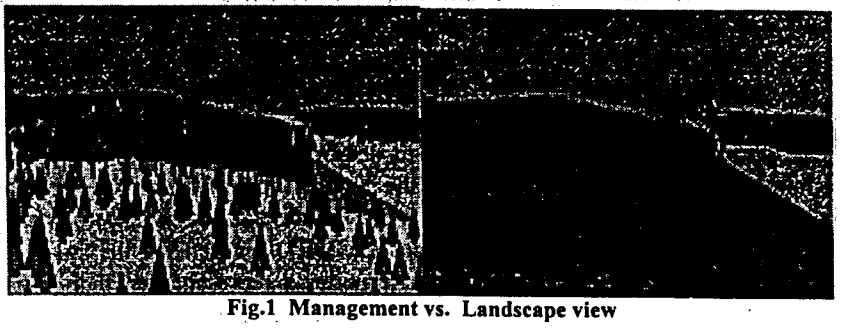

Fig.1 Management vs. Landscape view

Management mode provides a simplified (abstract) presentation of the real forest conditions that helps the manager quickly and efficiently to query and analyze the different characteristics of stands and single trees.

Reduced realism enhances the manipulability of the forest world, speeds the analyses and enables the user to observe detailed information over relatively large forest areas in one view. Landscape analysis mode provides a more realistic presentation of the real world, but typically has considerably longer response times. Trees are presented as texture-mapped objects and the ground surface is wrapped with scanned 2-D ground images (Fig.1)

For the present study, a comprehensive array of ground photography, ground video, laser rangefinder terrestrial survey, and traditional forest mensuration data were collected on a high elevation spruce forest site on the Dixie National Forest in southern Utah. This Midway Face viewshed was selected as part of a larger study of the visual aesthetic and recreational impacts of a spruce bark beetle outbreak in the area. From these data sources visualizations were developed to provide two levels of realism, the more abstract representations provided in the SmartForest *management view* and the more realistic representations provided by the *landscape view*. A regular grid-based sample of 15 individual sites within the Midway Face study area were represented, with 4 separate views (at 90-degree intervals) at each site. All 60 scenes were represented in both management and in landscape view. Examples of both types of visualizations are shown in Fig. 2.

Four separate panels of observers (college student volunteers at the University of Arizona) were shown either the management or the landscape views, and rated either the *perceived scenic beauty* or the *recreational quality* (overnight camping) for each of the 15 sites represented. In each case observers were shown the four views at a

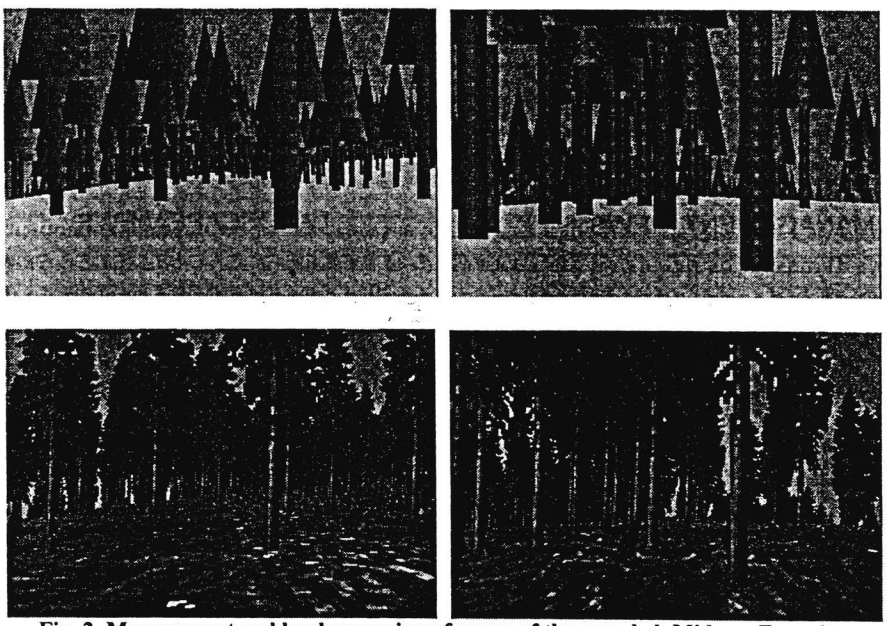

Fig. 2 Management and landscape views for one of the sampled Midway Face sites

site, and then recorded their judgments using a 10-point rating scale, where 1 indicated "very low scenic beauty (camping quality)" and 10 indicated "very high scenic beauty (camping quality)." Instructions acknowledged that these were computer generated "simulations" of a real forest site, and emphasized that observers were to "use the computer images to get an idea of what the forest would be like if you there" and to "rate the forest area, not the images themselves."

*Results-O*bserver ratings were compiled into computer data files and entered into the RMRATE program (Brown & Daniel, 1990) for psychometric scaling and analysis. Internal reliability coefficients (Tab. 1) revealed that observers were quite consistent in their ratings of recreational quality for both the management and the landscape visualizations. Ratings of scenic beauty, on the other hand, were substantially lower in consistency--especially for the more abstract management views.

Tab. 1 Internal reliability coefficients for perceptual ratings

	Management View	Landscape View
Scenic Beauty Ratings	0.55	0.68
Recreational Quality Ratings	0.91	0.85

Analysis of the relation ships between ratings based on the two different representation modes followed the same pattern (Tab. 2).

Tab. 2 Cross-Representational mode correlation coefficients

	Management-Scenic Beauty	Management-Recreat. Quality	Landscape-Scenic Beauty	Landscape-Reacreat. Quality
Management-Scenic Beauty	1.00			
Management-Recreat. Quality	-0.02	1.00		
Landscape-Scenic Beauty	0.12	0.80	1.00	
Landscape-Reacreat. Quality	0.05	0.85	0.90	1.00

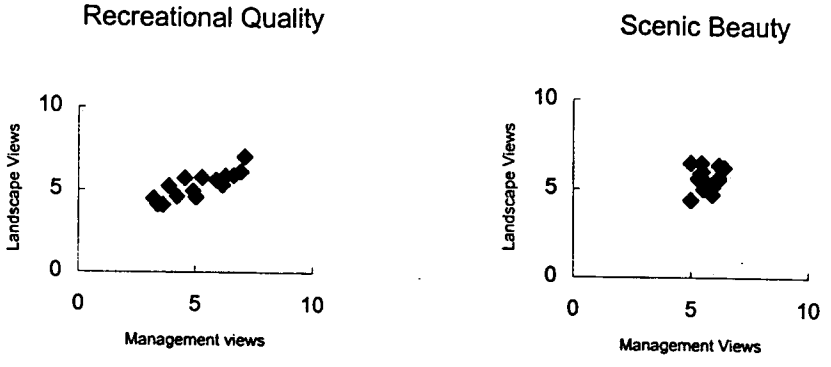

Fig. 3. Cross-visualization mode relationships for recreational quality (left panel) and for scenic beauty judgments (right panel).

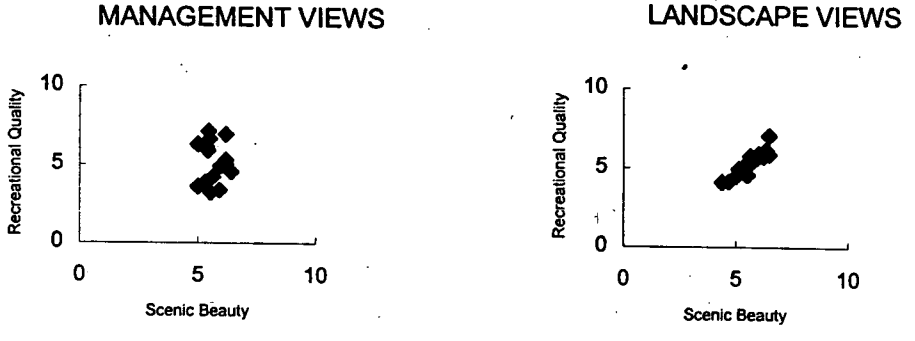

Fig. 4. Cross-perceptual dimension relationships for management views (left panel) and for landscape views (right panel).

Ratings of recreational quality based on management views correlated 0.85 with ratings based on landscape views, indicating high consistency of observer ratings between these two modes. Following the pattern of the internal reliabilities (and to some extent resulting from those internal reliabilities) ratings of perceived scenic beauty showed essentially no correlation (r =0.12) between management and landscape views. The difference in the degree of inter-mode agreement for ratings of recreational quality as compared to ratings of perceived scenic beauty is clear in the scatter plots in Fig. 3. Similarly, correlations between recreational quality ratings and perceived scenic beauty ratings for the management views were non-existent (r =-0.02). The same correlation between perceptual judgment dimensions for the landscape views was a very substantial 0.90. This difference is clear in the scatter plots shown in Fig. 4.

Conclusions--It appears from this study that the more abstract SmartForest visualizations, the *management views*, were insufficient for the purpose of obtaining public judgments of perceived scenic beauty. This condition showed the lowest internal reliability, and consistently produced the lowest intercorrelations with the other three visualization-perceptual dimension conditions. Perceived scenic beauty ratings based on the *landscape views* produced lower internal reliability ratings, compared to those obtained for the recreational quality ratings. However, as shown in Tab. 2, those ratings (as mean values for each site represented) did correspond quite well with landscape view-based ratings of scenic beauty and of recreational quality, and with recreational quality ratings based on the management views.

While this study can not confirm which, if any, of these rating sets is "correct" (with respect to direct on-site observations), the pattern of results would strongly suggest that observers had considerable difficulty rating perceived scenic beauty based on the more abstract management views. This finding is consistent with that reported by Daniel and Meitner (1997), where only high resolution, full color visualizations of forest scenes produced ratings that were both reliable and consistent with judgments based on color slides of the same scenes. Scenic beauty ratings based on color slides of forest scenes have repeatedly been shown to be consistent with ratings based on direct on-site experience (e.g., Daniel & Boster, 1976; Kellomaki & Savolainen, 1984; Shuttleworth, 1980; Zube, 1974).

Study 2 Public Perceptions and Expert Assessments: The Effects of False-Color in Forest Visualizations

Digital video images were developed to represent bark beetle hazard-relevant features of mixed spruce-birch forests in Alaska. Detailed inventory data and model projections were used to generate a series of scenes showing a single forest stand at different stages of succession and stand development. Changes in the relative dominance of hardwood (birch) and conifer (spruce) stand components represented five levels of ***Hazard***, ranging from Low to Very High. At each hazard level, other images depicted three to four different levels of ***Mortality***, ranging from None to High. The resulting images were modified to introduce false coloring to exaggerate the birch stand component. Separate groups of observers representative of the general public rated the *scenic beauty* of the scenes/conditions visualized. In addition, a sample of forest health management specialists estimated bark beetle *hazard* and *mortality* based on inspection of the visualized scene in either true or false coloration.

Procedure--The original visualizations for this study were created at the Imaging Systems Laboratory, University of Illinois. They were created to provide a visual aid to the Spruce Bark Beetle Expert System (Reynolds & Holsten, 1996), a training program to help forest health managers understand and assess spruce bark beetle hazard and risk for mixed spruce-hardwood stands (principally in Alaska). A digital image of a mixed spruce-birch stand on the Kenai Peninsula, Alaska was systematically modified using image processing systems to alter a) the apparent proportion of birch in the stand (an important hazard indicator) and b) the number of "dead" spruce trees visible in the scene (mortality). All other features of the selected forest scene remained unchanged.

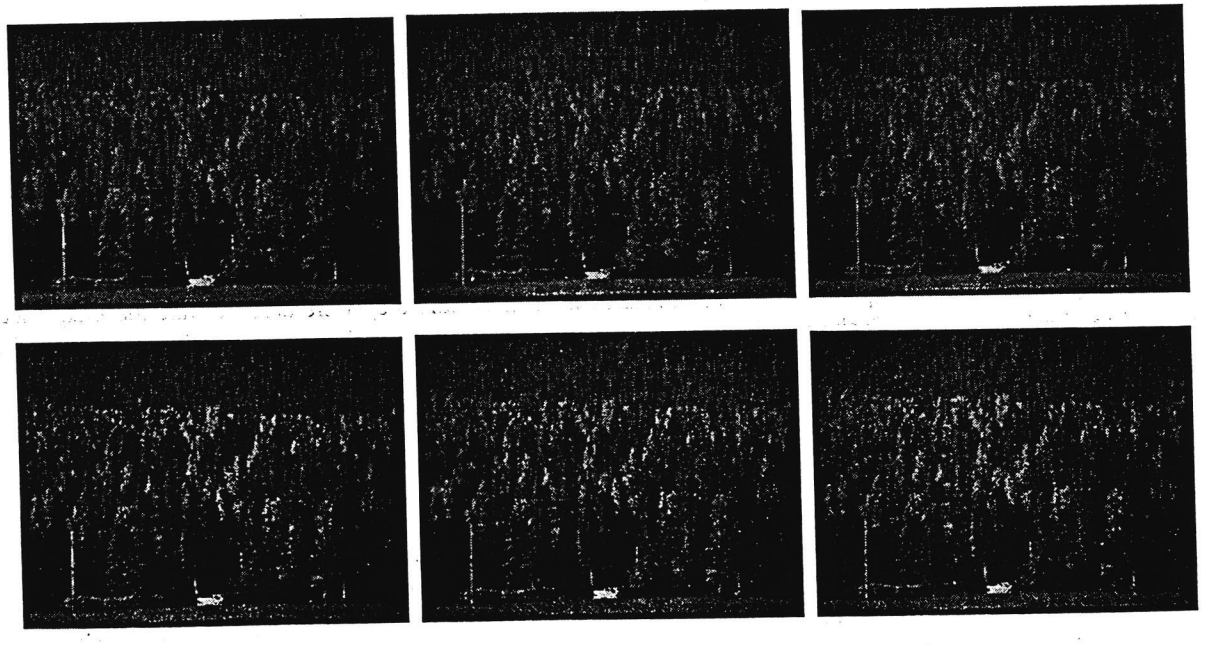

Fig. 5 Examples of "True" and "False" color images used in the study.

A total of 18 individual images were created, filling all but two cells of a 5 Hazard-level (Low, Low-Medium, Medium, Medium-High, High) by 4 Mortality-level (None, Low, Medium, High) factorial matrix. No images were created depicting High Mortality for either Low or Low-Medium Hazard forest scenes, where the numbers of spruce were insufficient to meet the High Mortality criteria. A parallel set of "false color" images was created at the Environmental Perception Laboratory, University of Arizona. To create these images a digital filter was first applied to isolate the birch component in the visible canopy (based on color and texture image characteristics that distinguish birch foliage from spruce). The color values (red, green and blue) of the isolated birch component (selected pixels) were then multiplied by a weighting function to shift the color a prescribed amount, producing a bright cyan coloration.

Thus, the previously lighter green, brighter foliage of the (true color) birch was shifted to a very bright cyan-blue, making that component very conspicuous in the scene (Fig. 5). Texture and shading features of the birch foliage regions were left essentially unchanged.

The resulting image sets were presented to observers representative of general public audiences (college student volunteers) and to forest health experts (professional foresters and forest entomologists) with varying degrees of training and experience in forest health assessment and management. For the student observers, visualizations were presented as high resolution full color images on a 68.58cm video monitor. Experts saw the images on pages of high-quality color prints (2 × 3 images to the 8 /12 by 27.94cm page; each image approximately 8.89 × 7.62cm).

Separate groups of student observers were shown either the True ($N = 24$) or the False color set ($N = 26$) of images. In each case, the order of presentation of the images was random, and a different random order was used for small sub-groups of observers (2 to 6) within each main condition. Both groups of observers were instructed that the images were "computer simulations" of a single forest scene, and that their task was to use the simulations to "get an idea of what the actual scene would be like if you were looking at it directly" and to "rate the scenic beauty of the forest (not the computer images themselves)." Scenic beauty judgments were recorded using a 10-point rating scale, where 1 indicated "very low scenic beauty" and 10 indicated "very high scenic beauty." Observers were further instructed that the investigators were interested in the "relative scenic beauty" of the various forest conditions represented, and that they should "try to use the full range of the 10-point scale" in making their judgments. The full set of 18 images was shown briefly as a preview prior to the recording of ratings.

The expert panels received a printed perceptual survey by mail. The survey package contained a set of instructions, response forms for recording ratings, a brief personal information form (regarding training and experience in forest health assessment in general and spruce bark beetle assessments in particular, previous experience with the particular set of images used in the study, and a space to record any comments about the task and procedures). The printed images were included in two separate covered, stapled booklets, one for the false color image set and one for the true color set. Half of the respondents were given the booklets in True-first, False-second order, and the other half received the booklets in the reverse order. Not all respondents completed the task, so that the final distribution was 12 observers in the True-first condition and 15 in the False-first condition.

No effort was made to disguise the fact that all of the images were of the same site, and the images were identified as "computer simulations" intended to give the observer an idea of what the represented site might be like under different forest conditions. Respondents self-administered the survey, and they were urged to rate the image sets separately and independently. Each set of images was arranged in a different random order, but the orders were the same for all true and for all false image sets.

Experts rated each set of images (true and false color separately) for both spruce bark beetle Hazard and for bark beetle-induced Mortality (number/proportion of dead trees). For the purposes of this study:

> **hazard** was defined as the *relative* amount (proportion) of mortality that is expected in susceptible trees over a ten year period following the onset of a (postulated) bark beetle outbreak; and
>
> **mortality** was defined as the *relative* number (proportion) of trees that are currently dead in the stand as represented.

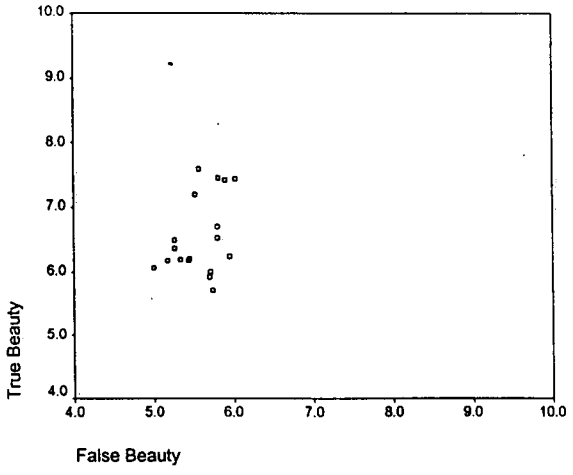

Fig. 6 Scatter plot of the relationship between ratings based on True color images (True Beauty) and False color images (False Beauty).

Both hazard and mortality were rated on a 5 point scale, where 1 indicated "very low Hazard (Mortality)" and 5 indicated "very high Hazard (Mortality)." Completed response forms were returned to the Environmental Perception Laboratory, University of Arizona by mail.

Results--Student scenic beauty ratings were entered into data files and subjected to psychometric analyses to assess the internal reliability of ratings within each image set. Cross-representation mode correlations were also assessed. In addition, the relationships of each set of ratings (True and False Beauty) to the levels of Hazard (5 levels) and Mortality (4 levels) specified in the Spruce Bark Beetle Expert System were investigated.

The internal reliability of ratings based on both the True and the False Color images was very high (.97 and .96, respectively). Thus, observers within each group were quite consistent in their ratings. However, the correlation between the two groups was a rather low .39, indicating that perceptual judgments of scenic beauty were quite different for True color versus False color representations. The essential lack of agreement between these two sets of ratings is shown clearly in Fig. 6.

Fig. 7 provides an indication of how the two rating sets differed with respect to their correspondence to the Expert System-specified levels of Hazard and of Mortality.

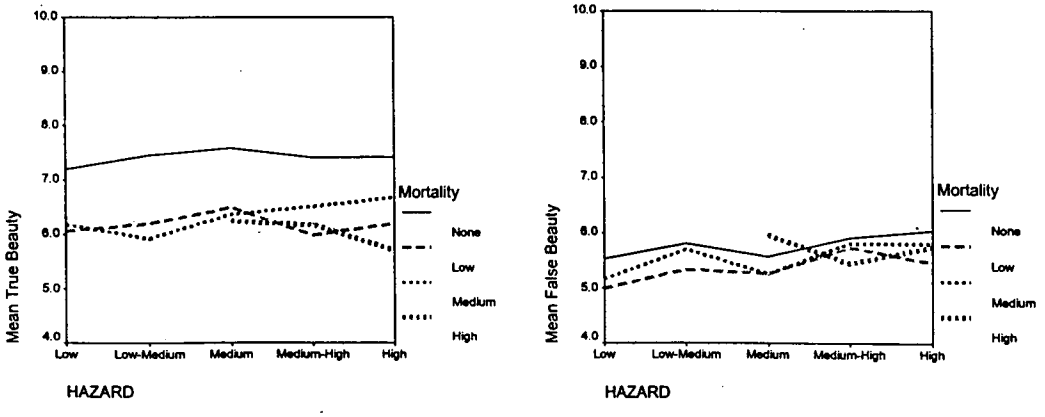

Fig. 7. True (left panel) and False Beauty (right panel) ratings as a function of specified Hazard and Mortality

Observers ratings of the True color images showed considerable effects of the Mortality variable, with the images displaying no mortality being clearly rated higher than any of the other images. The effects of the Hazard level variable were less clear, showing some trend toward a curvilinear (inverted U) relationship middle levels of hazard (more even mix of birch and spruce) tending to be preferred at all Mortality levels.

Ratings of the False color images showed little sensitivity to either Mortality or Hazard. There was, however a general trend for ratings to increase as Hazard increased, i.e., as the percent of birch in the image decreased. The effect of the false coloration (as compared to True color), then, appeared to be 1) the loss of the sensitivity of

scenic beauty ratings to Mortality and 2) an indication of a (weak) positive relationship between scenic beauty and Hazard-the fewer "blue" trees, the higher the scenic beauty.

Expert ratings of Hazard and of Mortality were both highly internally reliable, whether based on True or False color images, and whether rated first or second in the task, as shown in Tab. 3.

Tab. 3 Internal Reliability Coefficients for Expert Ratings

	True First	True Second	False First	False Second
Hazard	0.85	0.97	0.90	0.85
Mortality	0.97	0.97	0.95	0.97

Combining first and second order ratings, correlations between ratings of True and False images were very high for both Hazard ratings (r = 0.98) and for Mortality ratings (r = 0.98). In effect, experts rated the images the same, regardless of the true-false color differences (Fig. 8).

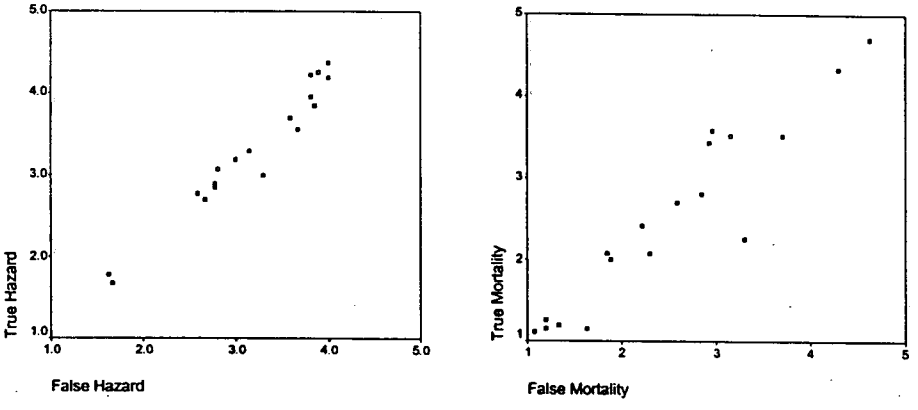

Fig. 8 Scatter plots of True-False Hazard (left) and True-False Mortality (right) ratings

Fig.s 9 and 10 show the relationships between the experts' ratings and the hazard and mortality levels specified in the Spruce Bark Beetle Expert System. In both cases the ratings follow the pattern that would be expected-greater specified hazard produces higher rated Hazard for both True and False images sets, and greater specified mortality produces higher Mortality ratings for both image sets.

Inspection of Fig. 9 reveals that experts took mortality levels into consideration when rating Hazard. Images with no visible mortality were consistently rated as having lower Hazard, and all levels of System specified hazard. Mortality ratings (Fig. 10) on the other hand were apparently not affected by the system specified levels of hazard.

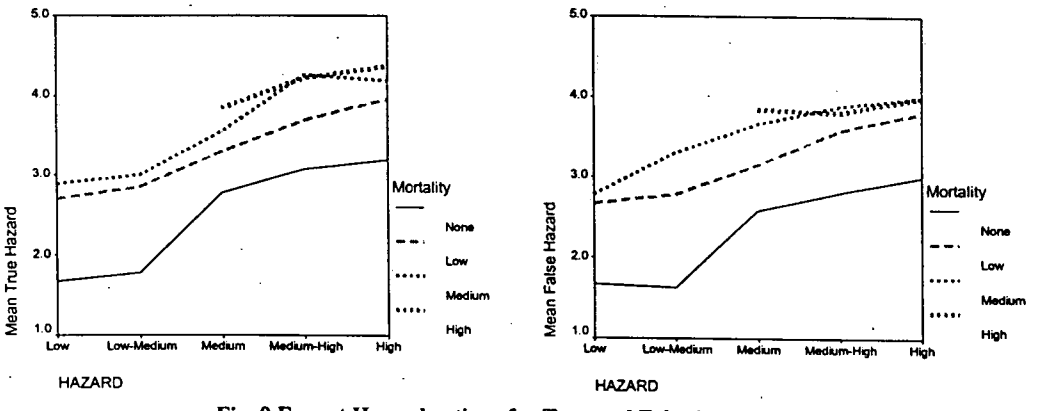

Fig. 9 Expert Hazard ratings for True and False image sets

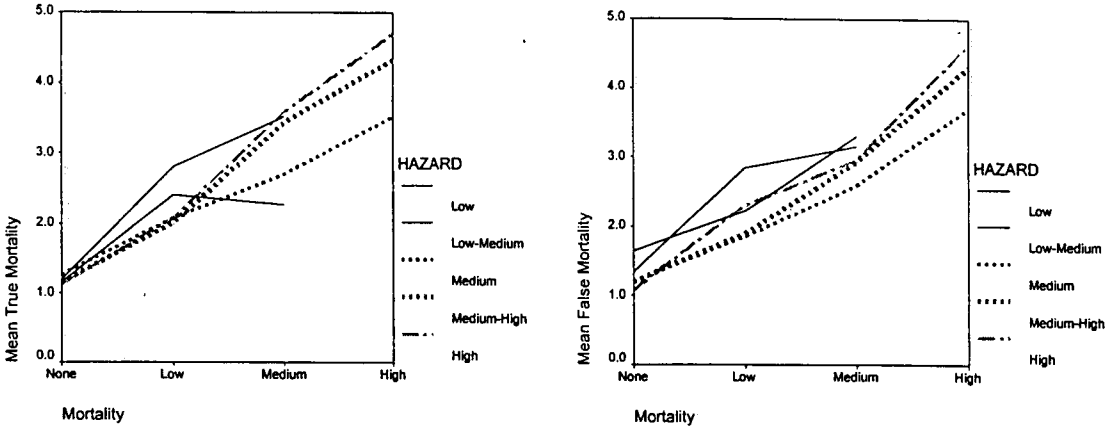

Fig. 10 Expert Mortality ratings for True and False image sets

*Conclusions-F*alse coloration had substantial effects on public perceptual judgments of scenic beauty. While both true color and false color images both produced highly reliable ratings (internally consistent), there was very little correspondence between those two sets of ratings of the same forest sites/conditions. In particular, false coloration tended to alter the relations between system specified hazard, so that higher levels of hazard were associated with higher scenic beauty. This was apparently due to the fact that images of the higher hazard levels (lowest proportions of birch) had fewer "blue" trees. Moreover, unlike the ratings of the true color images, ratings of the false color images were not sensitive to mortality-the differences between no mortality and the other levels represented being lost in the false color ratings.

Based on previous research, the true color images would be expected to produce scenic beauty ratings that are in good agreement with direct, on-site ratings. Analysis of the relationships between ratings and system specified levels of hazard and mortality were consistent with this assumption. Stands with a more even mix of birch and spruce tended to be judged as more scenically beautiful, and scenes with no dead trees were consistently rated higher than scenes with dead trees. These expected relationships were not obtained for ratings of the false color images. Based on these findings, it seems clear that false color images of the type studied here would not be suitable for determining public perceptual judgments of scenic beauty in forest landscapes. Indeed, this study (and related research such as Daniel and Meitner, 1997) suggests that modifications of true colors in forest visualizations could obscure important relationships between forest characteristics and public perceptions of scenic beauty, as occurred for the hazard and mortality variables studied here.

Forest health experts seemed to be relatively unaffected by the color change. Ratings of both hazard and of Mortality were very consistent both within and between the True and False color image sets. False coloration did not "help" experts make their judgments, and neither did it hurt. Ratings of the True color images were very consistent and in good correspondence with the system specified levels, and the introduction of false coloration of a key stand feature (the birch component) produced no improvement in these judgments. Of course, in situations where the critical forest features were less obvious, and where false colors were systematically related to critical stand features (as in more subtle defoliation situations where infrared or near-infrared photography can make this feature stand out) experts' evaluations might well benefit from "false coloration."

CONCLUSIONS

The two studies reviewed in this paper address possible situations in which computer data visualizations might be used in the context of forest health management, and call attention to the possible "pitfalls" of using visualizations that are inappropriate to the audience/questions being asked. In the first study it was found that visualizations with higher levels of realism are required for obtaining valid judgments of perceived scenic beauty of forest sites from general public audiences. At the same time less realistic (more abstract) representations were found to be sufficient for the same audience to make consistent and (apparently) valid judgments of recreational quality (overnight camping) for the same forest sites.

In the second study, false coloration of forest visualizations was found to substantially affect public audience's scenic beauty ratings of a forest scene as compared to true colors. Of particular concern here was the fact that expected effects of changes in stand composition (proportions of spruce and birch) and of the presence of dead trees in the scene were not found for the false color-based scenic beauty ratings. Forest health experts, on the other hand, were not affected by the changes in coloration. They were apparently able to "read through" the differences in the visualizations to provide sensitive and consistent ratings of spruce beetle hazard and mortality.

The particular visualization parameters investigated in these studies were only intended as proxies for the studies do, however, call attention to the possibly unintended effects that choices of visualization parameters (color fidelity, resolution, "realism") can have on the perceptions, judgments and decisions that both experts and public audiences might make based on those visualizations. An important conclusion from these studies is that care must be exercised in developing and using environmental visualizations to insure that the visualizations fit the audience and the management problem to which they are applied. Appropriate visualizations can help enormously to improve communication among experts and between experts and the public about complex forest management issues. Inappropriate visualizations, however, can lead experts and the public alike to come to invalid conclusions about the environments that they purport to represent, and could potentially mislead well intended forest health planning and management efforts.

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森林保健管理决策支持数据拟像化

Terry C.Daniel

摘　要

森林保健管理决策常常基于对未来森林条件和健康影响源影响的长期预测,这些条件和影响对于那些未受过培训或没有经验的森林保健管理员来说是复杂的、难于理解的。现代计算机环境数据拟像化系统对预测帮助极大,森林保健专家能在林分和景观水平上利用高速、低分辨率的分析拟像化相互作用地探索森林和森林健康变化的可见特性。多学科的森林管理队能对预期森林条件变化和森林健康源对这些条件影响达到更有效的相互理解。通过仔细观察，照片真实拟像化能使公众更好地理解和欣赏森林保健管理活动的动力和意图。本文利用最近完成和在研的项目作例子评价和评估森林保健管理过程中计算机数据拟像化。

VISTA SCENIC BEAUTY ESTIMATION MODEL
AN APPLICATION OF INTEGRATING
NEURAL NET AND GEOGRAPHIC INFORMATION SYSTEM

By

YU-LAN YUAN

A Thesis Submitted to the Faculty of the

SCHOOL OF RENEWABLE NATURAL RESOURCES

In Partial Fulfillment of the Requirements
For the Degree of

MASTER OF LANDSCAPE ARCHITECTURE

In the Graduate College

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ABSTRACT

There are some issues that have to be addressed for further understanding and improving scenic beauty management. First, the conventional model, preference rating based on fixed scene and direction, may not sufficiently reflect the reality of visual experience. Rather, visual and scenic preference is construed of a spatial experience. Second, the predictors are chosen based on measuring the composition of landscape features shown in the image. The measurement may not necessarily represent the contents of the physical environment. Third, judgements of scenic preference are complicated tasks. Simple linear regression analysis, with limited degree of freedom and some statistical constraints, may not represent the complexity of human judgments.

An integrated model was developed by integrating the Scenic Beauty Estimation (SBE) model (Terry, 1976), the geographic information system (GIS) and, the artificial neural network (ANN). The results suggested the integrated model might be utilized as an automatic scenic preference mechanism for policy making. Implications for future research are also suggested.

1 INTRODUCTION

Providing recreation and landscape scenic beauty has been a major mission in U.S. Forest Service management for the past 30 years (White House Conference 1965; the National Environmental Policy Act 1969). Magill (1990) pointed out that inadequate knowledge of the visual consequences of management actions, lack of management alternatives to satisfy public scenic demands, and inadequate knowledge of publics perceptions, expectations, concerns and demands for visual quality impede effective management of scenic beauty. Over the past 20 years applied science and technology has provided new methods and information that can facilitate scenic beauty management. This chapter describes relevant previous research and defines research objectives to explore new technology to assist scenic beauty management.

1.1 Problem Statement

Shuttleworth (1980) noted that actual on-site landscape experience involves movement through a three-dimensional environment. Most scenic beauty perception research, however, has used still slides or photographs with a restricted range of view, as a surrogate to elicit participants. Scenic preferences (Shafer et al., 1969; Shafer and Brush, 1977;

Buhyoff et al, 1978, and Sheppard, 1989). Bishop (1992) stressed that the estimates of the visual impact of landscape change should be based on its effect on locations, and not on specific circumscribed views. Therefore, the visual environment at any point should be considered as the entire 360-degree surroundings of the observer, rather than any specific restricted view.

Quantifying the visual quality of the environment presents problems because of the diverse environmental and psychological variables required to estimate or to predict it (Bishop and Hull, 1991). Research (Shafer et al., 1969; Shafer and Brush, 1977; Buhyoff et al. 1981) has tried to derive and quantify physical landscape variables by laying grid squares over photographs, and then measuring the area perimeter or other parameters of two-dimensional features on the photographs. This approach provides a "reliable and predictive tool" to predict scenic preferences from photographs. However measuring variables on photographs only gets the composition of physical variables as projected on a two-dimension "picture plane." Such measurement cannot be consistently related to the geographic locations of physical variables in the three dimensional world. Picture-based scenic beauty prediction models are, therefore, difficult to integrate into environmental management actions.

The majority of previous research adopted statistical methods to analyze the correlationships between identified

physical variables and scenic preferences (e.g. Kaplan, 1979; Kaplan et al. 1989; Gobster & Chenoweth, 1989; Steinitz, 1990; Shafer & Brush, 1977; Buhyoff et al. 1978; Bell, 1988, etc.). High R-square values showed chosen physical variables are adequate for predicting scenic beauty. According to Deardon (1980) there are three weaknesses applying statistical methods in such assessments. First is the assumption that the landscape can be reduced to a number of separate components and each component can be measured independently. Complex landscape components may not all be treated effectively as statistical variables, and statistical methods lack the ability to deal with interdependencies among variables. While both waterbodies and woods may separately increase scenic preferences, what combination of these features is the most preferable? Second, landscape appreciation is no less subjective than the "whim" of the designer. Third, measurement methods typically make use of nominal or ordinal scales, making the frequently arithmetic procedures depend on the data. Scenic beauty relationships are not necessarily linear; a scene that has twice the size of water body doesn't mean that it is twice as beautiful as another scene. Limiting the number of variables used in conventional prediction models result in simplifying the relationships among physical features. In addition, predictor physical features without spatial references make hard to quantify those features in management. It is, therefore, necessary to find an

alternative model that can possibly overcome those weaknesses and still maintain the strength of previous prediction models.

1.2 Goals and Objectives

Most scenic beauty modeling research has focused on near view perceptions, where viewers are located within the forest canopy, and their views are limited to a few hundred meters. Daniel (1995) has noted that there has been relatively little effort toward developing vista scenic beauty models, especially models that are based on geographically referenced physical features of forest areas that would typically be available from forest data bases or models. The goal of this research is to develop and examine an alternative model for vista scenic beauty prediction based on biophysical landscape features.

The specific objectives identified to achieve the research goals were:

1. To identify suitable physical variables from geographic databases that reflect the scenically relevant landscape features of forest settings;
2. To develop an appropriate presentation medium for eliciting vista scenic preferences;
3. To develop a neural network model to classify scenic beauty from geographical data.

4. To examine the predictive ability of the neural net-based SBE model to predict scenic beauty in a wilderness settings.

2 REVIEW OF LITERATURE

2.1 Scenic Beauty Estimate Method

Scenic beauty is a product of a human observer' response to his/her surrounding landscapes (Zube 1987). Scenic beauty is affected by physical features, such as topography, vegetation patterns, slope and aspect, and by observer characteristics, such as motion, personal background, location, and view angle. A quantitative scenic beauty assessment model can be developed for a given (ideal or average) viewer if the products (scenic preferences) and the causes (the physical and tangible landscape variables) can be identified. If scenic preferences can be associated consistently with the physical landscape features, then, the latter can be used as a predictor of the former. There has been a tremendous amount of research on visual quality assessment and scenic beauty prediction based on this assumption. (e.g., Daniel and Boster 1976; Shafer and Brush, 1977; Zube et al 1989; Gobster and Chenoweth, 1989; Steinitz, 1990; Kroh and Gimblett, 1992; Bishop, 1992). One of the major efforts is the Scenic Beauty Estimate Method (SBE), introduced by Daniel and Boster (1976). It provides a precise quantitative measurement and predictive model that can be easily integrated with other resources management

technologies. Participants use a rating scale to report perceived beauty values for landscape scenes or photographic surrogates of those scenes. Once scenic beauty estimates are obtained, statistical analyses are used to relate variations in perceived scenic beauty with variations in the physical landscape variables. Many studies have applied the basic scenic beauty estimation approach and obtained good prediction ability (Brown and Daniel 1984; Dearden 1980; Rise, 1990). A detailed discussion on Scenic Beauty Estimation methods (SBE) can be found in Daniel and Boster (1976), Brown and Daniel (1984), Hull (1989), Hull et al. (1984), and Bishop and Hull (1991).

2.2 Artificial Neural Networks Model

Although traditional statistical techniques, such as multiple linear regression and logistic regression, play an important role in SBE methods. They suffer from several weaknesses as mentioned before those limit their effectiveness. Techniques have been developed to improve those weaknesses. One of those techniques that have been in existence for nearly fifty years are Artificial Neural Network (SNN) models. ANN models have been applied in a variety of disciplines. Applications of ANN for resource assessment begin to present its potential in the late 80s' as a landcover classification techniques (Hepner and Ritter 1989). Recently,

ANN has been readily adopted in many fields where problems cannot be efficiently solved by using traditional approaches. Those problems include landscape planning (Gimblett et. al, 1996); recreation opportunity assessment (Gimblett et al, in press); landscape/architectural design (Coyne & Yokozawa, 1992); prediction of visual quality (Bishop, 1994); landuse suitability (Wang, 1993); travel decision-making (Jeng, 1994).

ANNs' are based on mathematical models that tend to mimic brain-like functions to process information. ANN's organized data, analyze statistics, spot trends, adapt and learn from the data, take corrective control action, and predict future products (Nelson & Illingworth, 1990). The neural network technique can be thought as an advanced form of the traditional regression models that are currently used to solve many environmental problems. In landscape analysis situations, the integration of ANN with GIS has proven to be a viable approach for resource assessment and prediction tool when compared to conventional regression approaches (Aim & Gidalizon, 1990; Steinitz, 1990; Brown, 1990; Lynch & Gimblett, 1992; Hadrian, 1988; Bishop & Hull, 1991).

A neural network is a statistical technique that calculates weights for predictor characteristics (e.g. slope, visual area) by `self learning' from data examples (participants' landscape preferences). When the comparing NN based models with regression models the following characteristics of neural networks have been found. First,

unlike regression models, neural networks learn by example to solve problems rather than applying preprogrammed algorithms. Second, neural nets can process complex nonlinear relationships even when the input information is fuzzy, incomplete, noisy, and imprecise. Third, ANN requires fewer data resources than other techniques; for example, the more variables a regression model has, the more difficult it is to arrive at a stable model solution. ANN can handle an immense number of variables, therefore, it is suitable to be employed in simulating relationships in complex, non-linear spatial data analysis, especially in a GIS context. Fourth, specific distribution assumptions of the input data are not required as for statistical approaches. This characteristic is very useful in scenic beauty modeling, because the input data is often incomplete, and may not quality for the statistical assumptions (Openshaw, 1993). Furthermore, once neural nets are built, they can be updated continuously with new data to improve performance. Although some research has considered the training time of the neural nets to go quite long, the training of a neural net usually can be quickly accomplished. Bishop (1994) suggested that a neural network used in scenic beauty prediction had better performance than traditional statistical approaches.

Back-Propagation Neural Networks

During training, neural networks employ an effective

technique that learns relationships through repeated exposure to data and adjustments of the weight values. Although there are many training methods exist, the back-propagation neural network (BPNN) model developed by Rumelhart et al. (1986) is one of the most successful approaches, used in this study to illustrate how the neural computing technology can be combined with GIS modeling for scenic beauty prediction. BPNN was named by the way it processes the errors created by forward propagating the input through the hidden layer(s) to the output layer. Error is determined at the output layer, and then the errors are propagated back through the network from the output layer to the input layer.

How they work

Typically, Back-Propagation neural networks have at least three interconnected levels. The first layer is mad up of predictor variables, so called input (e.g. landcover, relative elevation). This layer processes the predictor variables entering the network for learning or training. The middle layer contains processing elements that include transfer functions. This layer allows neural networks to model non-linear data. Also, process elements in the middle layer can be viewed as derived variables that pass information to the next layer. The third layer produces the neural network output or the predicted outcome (e.g. landscape preferences, scenic beauty value).

As mentioned before, A BPNN consists of a number of processing elements called nodes (or PE). Its architecture includes one input layer, one or many hidden layer(s), and one output layer (Figure 1). A node is an elementary processing unit. Organized nodes form layers. The connections between nodes are associated with variable weights. All the nodes, besides the input nodes, have two functions. The first function of the node is to receive data from the previous layer, and the second is to launch an activation to successive nodes after the input data has been processed. Nodes of the input layer process input data by activation and pass activated signals to successive nodes. Figure 2 shows a simplified neural network. That is, the nodes of the input layer can be considered as sensors of people that receive stimuli (viewing scenes) from the surrounding environment. The nodes of the output layer can be thought vary responses of people (e.g., preferences).

BPNN has to be trained (or learn). Training requires input and desired output training pairs. The neural network findss patterns associating the given input with the desired output. This is so-called "supervised training". Additionally, training of a neural network adjusts the connection weights systematically to establish the desired input-output relationships.

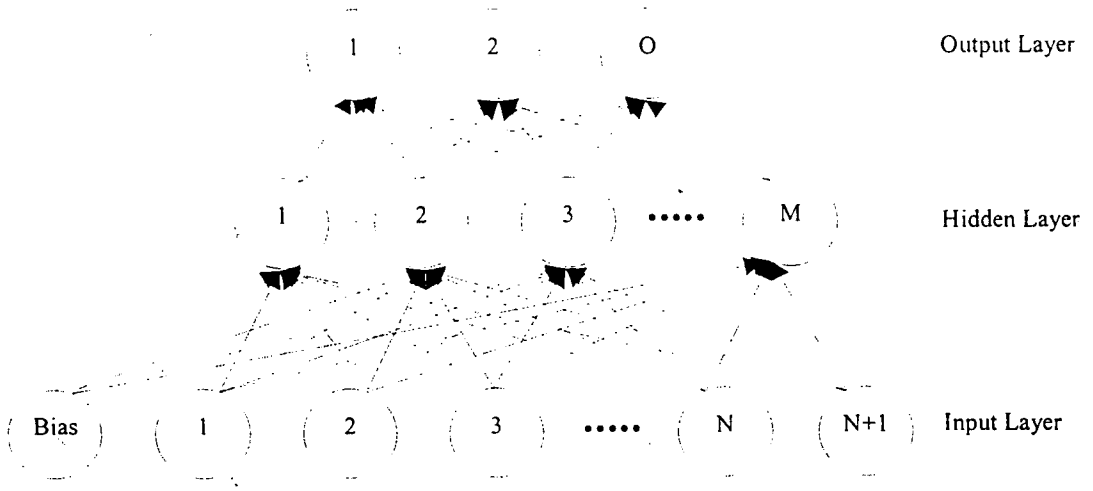


Figure 1 A general neural network (n, m, and o are very depending on the input variables and output classes)

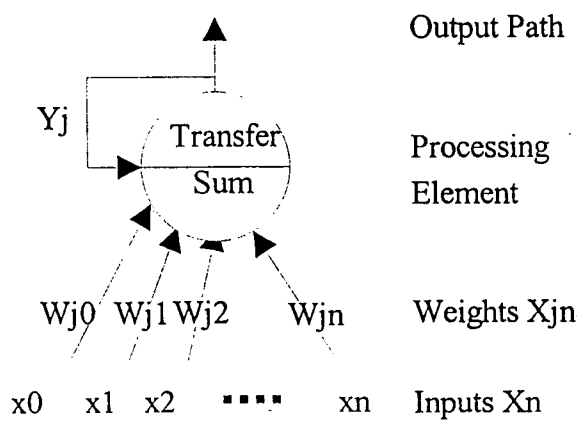


Figure 2 the processing function of a single node in a network. Each input connection has associated with variable weight. The output corresponds to the desired solution or work as the input to another nodes. ($I = \sum Wji Xj$ Summation, $Yj=f(I)$)

2.3 Geographic Information Systems

To manage landscapes effectively, environmental data is required that accurately represents the geographic distributions of relevant features (Gimblett, 1990), Computer-based operating software packages, GIS, are designed to input, store, retrieve, process, analyze, and display geographically distributed information efficiently and systematically. Many researchers have integrated GIS into the modeling of visual quality (Bishop, 1992, 1994; Wyatt and Itami, 1994) and visual resource management (Bishop and Hull, 1989).

Applying GIS on vista scenic beauty models can satisfy the following purposes:

1) The storage of accurate data representing on-ground conditions provides the ability to extract physical variables, such as slope, aspect, and geographic orientation. GIS presents three types of information about real world objects; a) their position with respect to a known coordinate system; b) their attributes, such as vegetation type and elevation, and; and c) their spatial interrelationships with each other (Burroughs, 1986).
2) The systematic analyses of spatial geographic relationships use a set of functional capabilities.

They include matrix algebra and neighborhood analysis (Wissler 1993).

3) Data can be imported from external sources and can be easily updated to provide new information assisting management decisions.

4) It provides an interface for users to manipulate geographic information.

5) It yields cartographic products so that the results of analyses can be easily presented and communicated with experts and clients.

Owing to these characteristics, high levels of accuracy of spatial analysis can be achieved. For example, a given viewpoint can be delineated, the visual frequencies, the location, area, attributes and spatial relationships of physical features and the relationships between given viewpoints and those physical variables can be identified. This information can be used to reflect the features of the real 3-D world into the "picture plane" to determine effects on views from specified viewpoints.

Summary

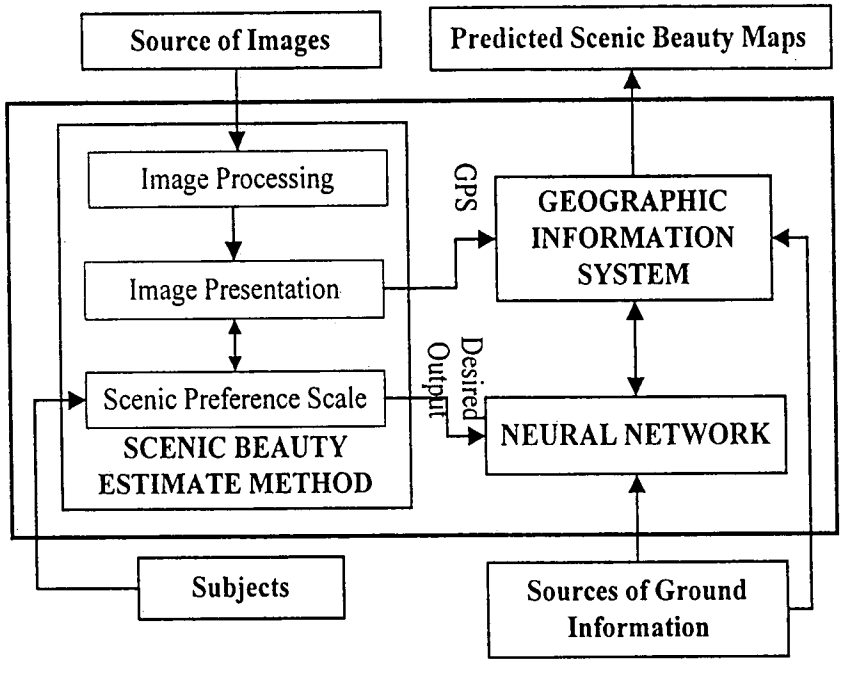
GIS is a useful tool for spatial data analysis and management. Quantified and geo-referenced physical features from GIS can be used to map and understand the spatial relationships among variables. These types of data can be used as physical variables of an ANN. The physical variables

comprise the landscape for the input to a neural network model. Scenic beauty preferences are contributed as the desired outputs of the ANN for training. An ANN offers many advantages over traditional regression approaches. It explores and identifies the relationships between scenic preferences (desired outputs), and landscape features (inputs); by knowing which photographic stimuli have been taken and SBE acquiring ratings from these view-based locations. It is possible to incorporate an ANN with SBE model and to predict scenic beauty in wildness settings, especially, vista scenes. Together, the SBE method, GIS and neural network model have great potential to strengthen vista scenic beauty prediction abilities.

3 RESEARCH METHODOLOGY

This chapter describes the methods employed to adhere the goals of the research. This chapter is presented in three parts: vista scenic beauty estimation, geo-spatial data analysis, and neural net modeling. The basic concept is shown in Figure 3.

Figure 3 the concept of the Neural-Based Vista Scenic Beauty Model



3.1 Vista Scenic Beauty Estimation

This study was aimed at developing a better understanding of the relationships of landscape features to human scenic preferences. Scenic beauty estimation methods were used to elicit and to quantify scenic preferences from observers. Vista landscape scenes (panoramas) were used to represent the studied landscape areas.

Observers

Previous research (Daniel and Boster 1976, Arthur 1977) has shown that scenic judgments by students and by the general public are highly correlated. Although individuals vary in their scenic preferences and perhaps due to their cultural backgrounds, active purposes etc; there is still substantial agreement across varying groups with respect to scenic preferences (Zube et al, 1982). Although individual differences are important, it is useful to first understand general trends. For this reason, differences among people will be considered as "noise" in the data. In addition, the purpose is not to generalize the universal phenomenon, but to test the feasibility of using neural network models for the purpose of predicting scenic beauty. Thus, it is reasonable to derive "average" scenic beauty judgments from groups of students to represent general public scenic preferences. Students from the University of Arizona with a wide range of backgrounds,

therefore, were selected to be the subjects for the preference experiment.

Measurement scale.

A 10-point rating scale (0-9) was used to report scenic beauty judgement, where a 9 indicated the highest beauty, and 0 indicated the lowest. Five problems associated with interpreting rating scale responses have been identified: unequal judgment criterion scales (origin differences), lack of interobserver correspondence, linear differences between criterion scales (interval size), lack of intraobserver consistency, perceptual and criterion shift (Brown and Daniel 1990). These problems can be solved and controlled through careful research design and statistical processes. If scenes are consistently rated by an observer, then the relative ratings will reflect perceived differences among those scenes. In order to partial out intraobserver inconsistencies and perceptual or criterion shift effects, the assumption was made that any two people who rate scenes in the same relative way have the same perception of scenic beauty, even if their absolute ratings differ. Differences among observers' relative ratings are treated as "error" (statistically) or "noise" (neural net concept) in the scenic beauty data (output).

Additionally, the problem of unequal judgement criterion scales was ameliorated by presenting a set of individual "preview" images sampled from four directions from each

panorama. The previews depicted the range of characteristics represented by the panoramas subsequently to be rated and allowed subjects to establish appropriate rating criteria for the rating session (Brown et al, 1990). Still, different observers may use the 10-point rating scale differently, but "perception is a relatively consistent process that is strongly related to the features of the stimulus" (Brown & Daniel 1990). Thus, linear differences among observers' ratings were fallen to indicate differences in rating, not differences in perceptual preferences. Therefore, the second problem, lack of interobserver correspondence, can be solved by preprocessing scenic ratings to a common standardized scale before using as the output of the ANN. RMRATE, a useful statistical package, was utilized in this study. The detailed explanation of RMRATE can be found in the papers Brown and Daniel (1990) and Brown, et al (1990).

Vista Sample

There were four considerations involved in the selection of vista for the study. The first was that views should be typical of the study area forest landscape with diverse scenic qualities. The second was that views should be relatively extensive covering larger diverse forest areas. The third was that the features in the view should be representative of those relevant to managers and planners. According to these considerations, twenty-one vistas (viewpoints) were selected

to represent vista views in the high-elevation spruce forest study area.

Computer presentation was used to provide 360° panoramic views to represent each viewpoint/viewshed. The panoramic presentation allows viewers perceiving any direction of scenery from the viewpoint. Subjects were able to control the time spent on each segment of each panorama.

The presentation images were obtained by the following procedure. At each selected viewpoint, camera with a 35 x 50-mm lens was mounted and leveled on a tripod to reduce vertical frame shift. The tripod was kept stationary and the camera was rotated 360° clockwise starting from due north. Each slide in the panorama overlapped (approximated 10°) with adjacent slides so those 16 single frames fully cover a panoramic view. Sun angle and sun direction coupled with shutter speed and exposure were factors that affected the quality of individual slides within a panorama. Therefore, image processing was required before the 360° panoramas could be composed and presented to observers. The purpose of image processing was to create a non-overlapping full 360° representation of the view with equivalent photographic quality exposure of all the images in each panorama.

Two image-processing packages were used to preprocess images. Adobe Photoshop was adapted to crop and mosaic

individual photo images into a 360° panoramic view. Brightness, color, resolution and image size as well as other unmanageable factors (e.g. sky color, cloud, car, etc.) were normalized and adjusted and the images were transformed into an 800x600x256 with 8 bits color format.

PANA (Environment Perception Laboratory, 1995) is a computer program specially developed for presenting panoramas on a PC computer screen. PANA allows observers to use arrow keys to look back and forth within a 360° panorama.

A compass appeared in the lower right corner of the screen to indicate the view direction and, thus, which segment of the panorama is being presented. Subjects can look at each part of panorama as often and as long as they wish. When subjects decide to give their ratings, they simply press the Escape key. The screen presents the rating scale from 0 (very low scenic beauty) to 9 (very high scenic beauty) and asks the subject to enter their rating for the panorama they just viewed by pressing the appropriate number key. After the subjects enter their rating, they press the space bar to proceed to the next panorama. Subjects continue this procedure until all 21 panoramas are rated. PANA records the viewing time each subject spends on each segment of the panorama. It also records scenic beauty ratings that the observer assigns to the panorama. The time a subject spends on each segment of a panorama was hypothesized to reflect the importance of that

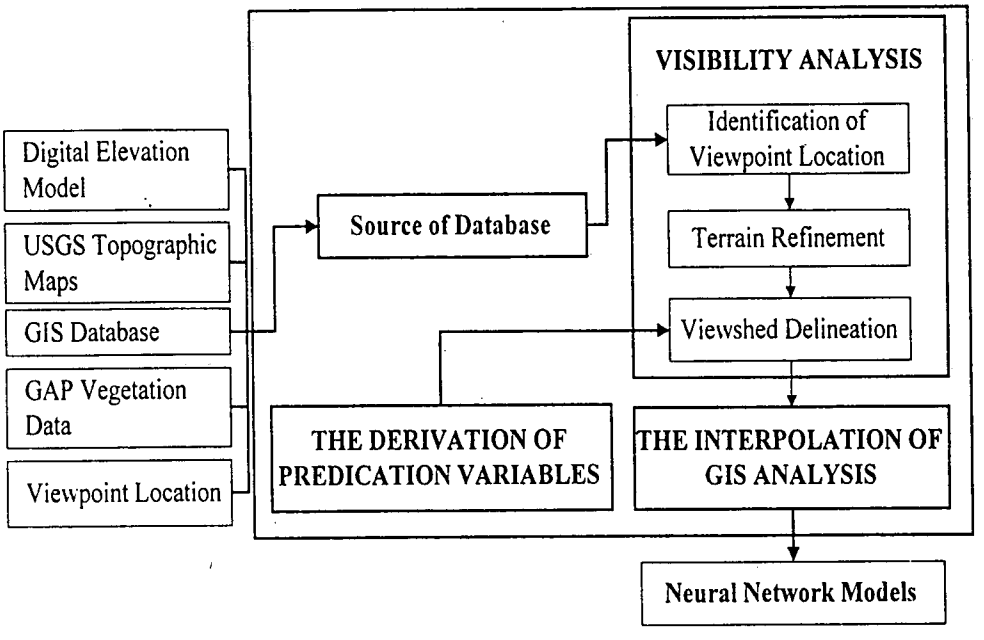
segment of the view.

A follow-up questionnaire was included to help identify positive and negative landscape features and characteristics which observers considered to have affected their scenic judgments. The positive and negative landscape features reported were used as a reference for deriving physical predictor variables from the spatial database. The questionnaire was completed after the participants finished the scenic rating.

3.2 Geographic Data Manipulation

Geographic data manipulation included three steps: 1) GIS database sources, 2) the derivation of predication variables, 3) visibility analysis; and 4) GIS database interpretation. Figure 4 shows the procedures involved in geographic data manipulation. The terms used here to represent GIS functions refer to ARC/INFO (Environmental System Research Institute, 1987) software, which was used in this study. Figure 4 illustrates the procedure of geographic data collection, manipulation, and analysis.

Figure 4 the procedure of geographic data collection, manipulation and analysis.



GIS Database Sources

The study area is located in Cedar City District of the Dixie national forest, Utah (Figure 5). The area contains woods on relatively flat terrain, hills covered with trees (some showing evidence of insect infection), grassy meadows, several stream beds with marshy areas, two major lakes, several ponds, roads, trails, peaks, and a few man-made structures. The original data was provided by the Dixie

National Forest, Utah. Data included USGS Digital elevation model (DEM) on a 30 by 30 square meters grid resolution, USGS 1:24,000 topographic maps, GIS data base in vector format (district boundaries, waterbodies, streams, and roads; Figure 5), and GAP vegetation cover data (Figure 7). Sample viewpoints (Figure 8) were recorded on USGS 1:24,000 topographic maps, and covered four quads, Brian Head, Navajo Lake, Panguitch Lake, and Henrie Knolls, representing a proximately 635.68 km^2 (Figure 9).

Predictor variables were derived from the above-mentioned sources. A study area boundary layer derived from a mosaic of the four USGS 1:24,0000 topographic maps, served as a basis for integrating data in different formats and scales.

Figure 5. The Location of Study Area

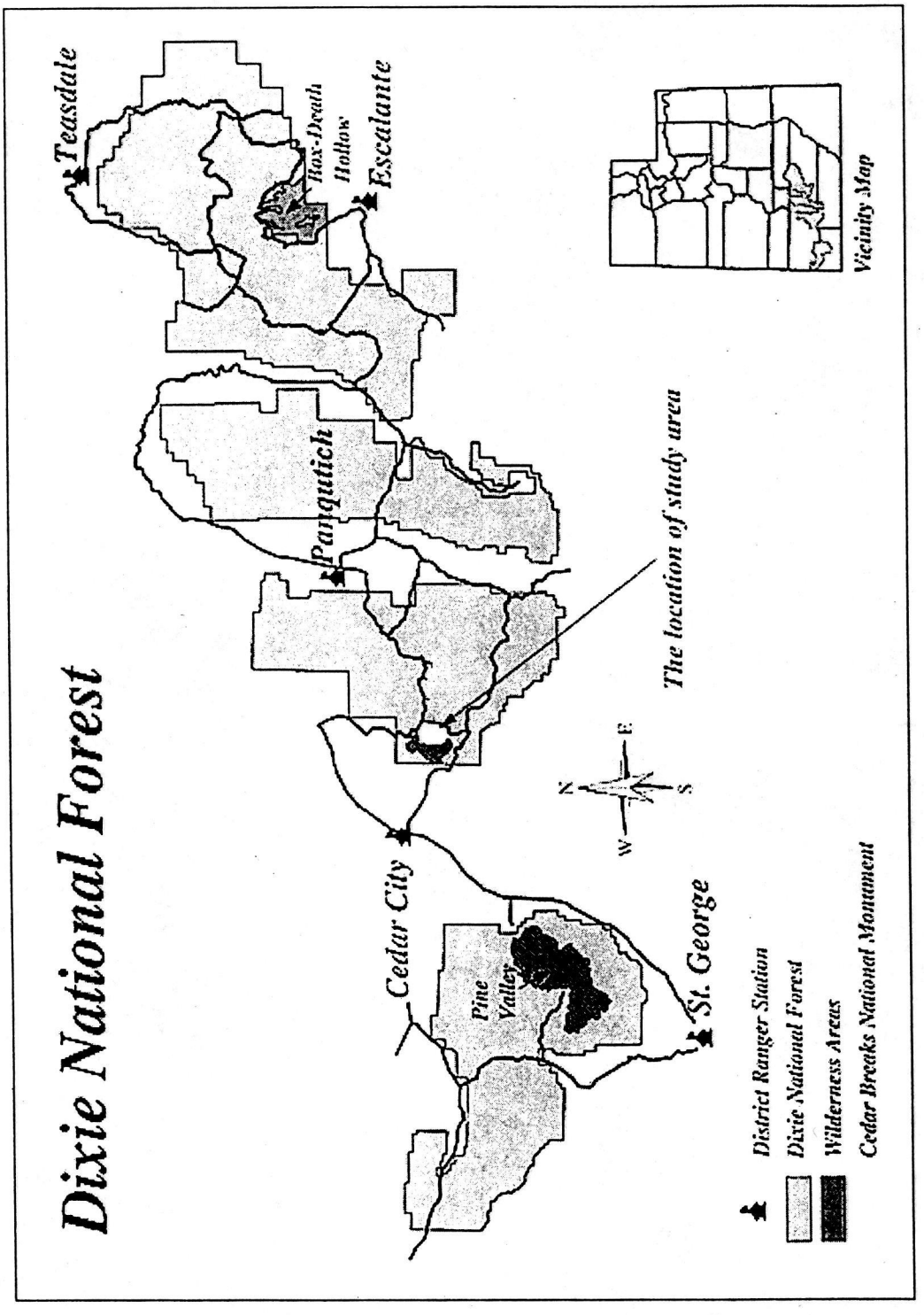


Figure 6 The physical elements that were derived from GIS database.

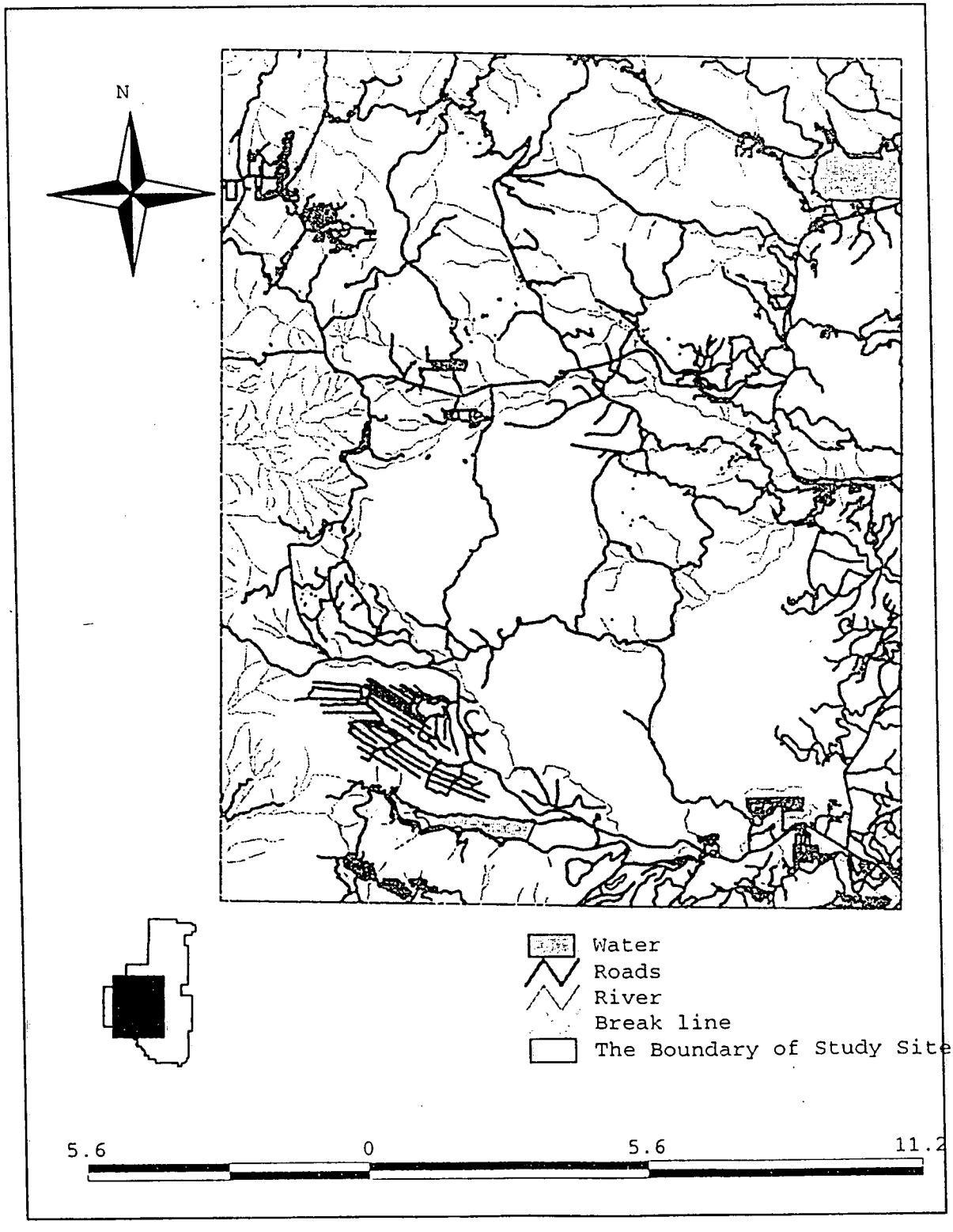


Figure 7 The Positions of the Sample Veiwpoints

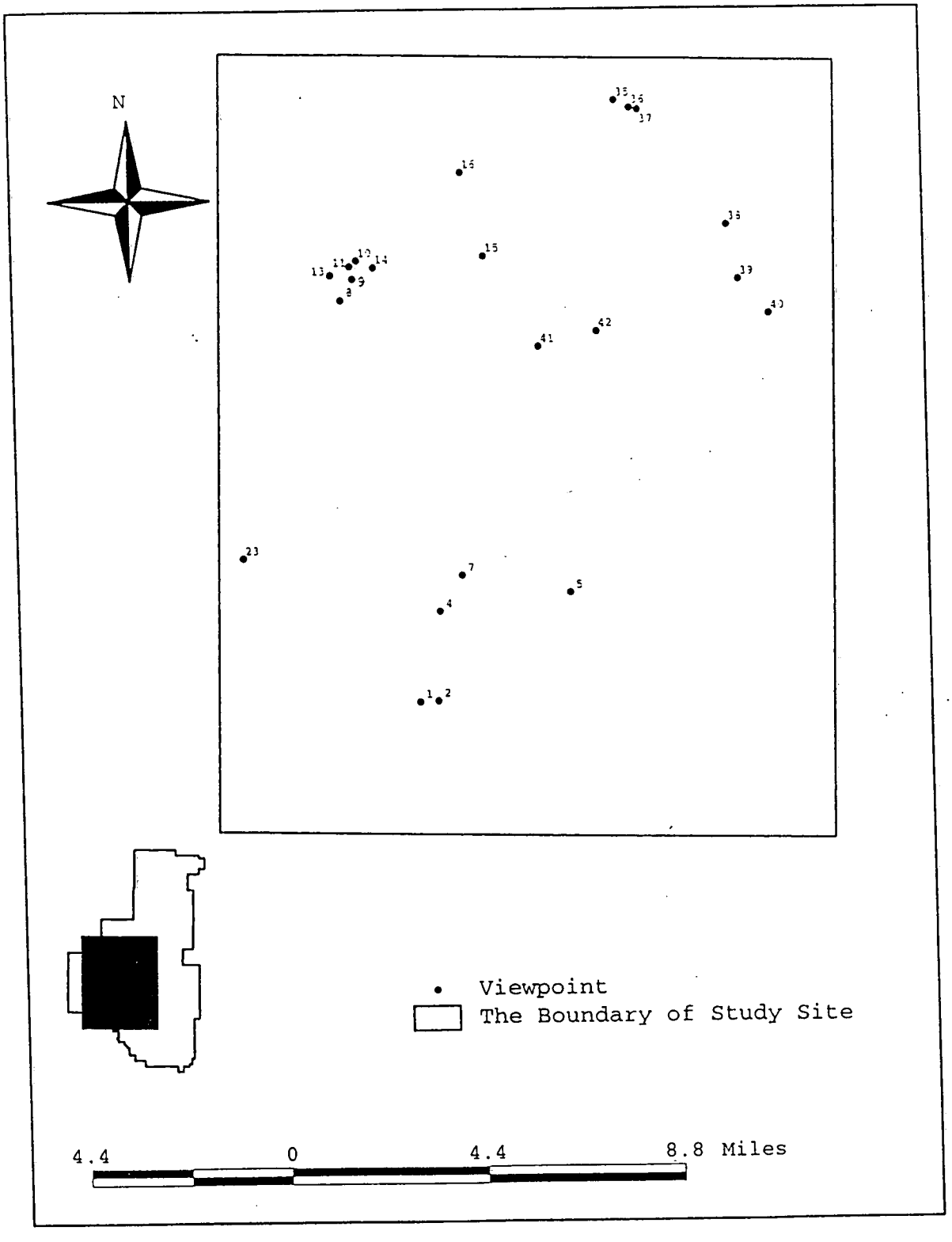
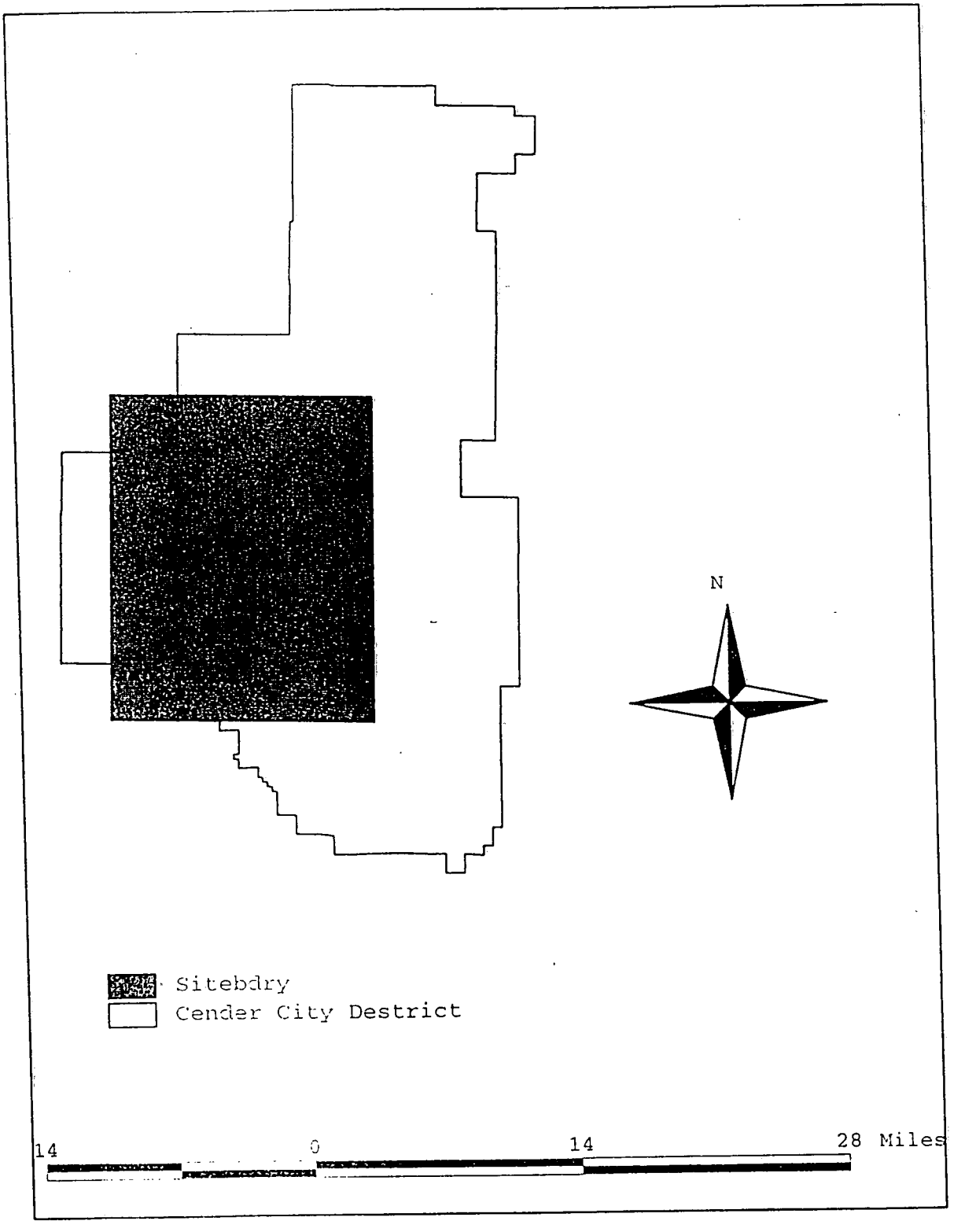


Figure 8 The Area of Study Site.



Derivation of Prediction Variables

Based on review of earlier research (Martens, 1890; Higuchi, 1944; Lynch, 1960; Litton, 1968; Norberg-Schulz, 1971) and considering what variables might potentially be integrated into management actions and be analyzed by GIS operators, this study utilized predictor variables and hierarchical relationships explained as follow:

1. Visibility: Areas that can physically be seen from a given viewpoint. Only physical features that can be seen can have influence on scenic beauty judgments. The total area of the landscape visible from a given viewpoint is defined as the viewshed for that viewpoint. Additionally, the SBE model is a viewer-based model. The location of viewer, therefore, affects how and what viewers might perceive from surrounding visual environment, and also affects interpretation of another physical variables' appearances.
2. Distance. Distance is an important physical variable, which has influence on the appearance of other physical variables. In terms of resolution, the farther the distance of objects from the viewer, the lower the visual resolution can be.
3. Topography: Topography provides the basis for slope, aspect, elevation, and the "roughness" of the

landscape. An area is more to the viewer when it has steeper slope. There are two types of aspects: absolute aspect and natural aspect. The natural aspect is the relative relationships of the faces of terrain surface to the polar system. The relative aspect is the relative relationship of the terrain surface (slope) to the line of sight from viewer's location.

4. Physical features. According to past studies (Daniel and Boster, 1976; Arthur, 1977; Buhuoff and Wellman, 1980; Schomaker, 1979), scenic beauty Judgments are consistently related to identifiable features of the landscape, such as vegetation patterns, the area of dominate vegetation types, waterbodies (pond, lake), rivers, roads (paved, unpaved, trail) and their orientations toward the observer.

Table 1 defines each landscape (input) variable as represented for quantitative analysis in the GIS. Total forty-three predictor variables were resulted by the three distance zones, as listed in Table 2 and 3.

Table 1. Predictor Variables in Whole Viewshed

[illegible]	[illegible]
Whole Area of a Viewshed	Total Visible Area
	Average Elevation
	Relative Elevation
	Roughness

Table 2 The definition of physical features used in prediction model.

Visible Area	The totally visible area (viewshed extent) in square meter
Distance	The distance is classified to foreground (0-500m), middleground (500-4400m), and background (4400m-40000m).
Slope (%)	The average slope within a viewshed
Natural Aspect	The measurement of surface orientation defines by the polar system.
Absolute Aspect	The absolute measurement from viewer to the orientation of objects.
Bearing	The relative locations of objects to viewers.
Vegetation Patterns	The number of visible vegetation species within a viewshed.
Dominate vegetation	The ratios of area of dominant vegetation species devide the total visible area.
Waterbody	Visible waterbody area, including lack and pond.
River	Visible river.
Roads	Visible roads within veiwshed, including paved and unpaved roads, and trails.
Majority Elevation	The majority elevation in a viewshed. That is median in terms of statistics.
Relative Elevation	The difference between the elevation of viewpoint and mean elevation of a viewshid.
Mean Elevation	The average elevation of viewshed.

Roughness of Topography	It is determined by the elevation variation within viewshed. That is std. in terms of statistics.

Table 3. Predictor Variable in Each Distanced Viewshed

Foreground Middleground Background	Absolute Aspect
	Natural Aspect
	Visible Area within background
	Average Elevation
	Relative Elevation
	Majority Elevation
	Slope
	Roughness
	Waterbody
	Rivers
	Roads
	The Number of Vegetation Types
	The Area of the Dominant Vegetation Type

Visibility Analysis

The visibility analysis consists of four steps to transfer GIS database into a neural network suitable format. There were: 1) identification of viewpoint location, 2) terrain refinement, 3) viewshed delineation, and 4) interpretation of physical variables.

The first step was to locate each viewpoint position so the landscape feature information reflects the "picture plane" views. The second step was terrain refinement. Visibility

analysis adopted a grid (cell) concept to represent a continuous surface consistently geo-referenced. Cells in each GIS theme were assigned unique values indicating its attributes. The value of each cell in the elevation theme, for example, indicated its elevation. Presumably, the finer terrain might have the smoother transformation of surface elevation from cell to cell. Abrupt elevation change from one grid to its neighbor cells might rarely happen. The terrain for visibility analysis was generated on in the basis of a 30 X 30 square meter USGS DEM. The resolution was considered too coarse. Additional information was required to refine the topography, which included 1) the highest and lowest points on the ground, 2) river (or stream) lines, 3) ridge and 4) the elevation of waterbody, and 5) other important points. Two terrain maps were built using different percentage of important points, 7lattice used 7percent of important point and 50lattice used 50 percent of ground important points. The comparisons were undertaken to find out which terrain is more suitable to represent visible topography (Table 4).

Table 4 The Statistical Comparison of Two Terrains with Different Dot Density

[illegible] Terrain	Low Dot Density (7lattice)	High dot density (50lattice)

Minimum	2330.88	2330.88
Maximum	3453.50	3453.63
Mean	2828.51	2828.50
Standard Deviation	213.56	213.55
Covariance	45234.99	45191.51
Correlation	.9990	.99903

There were no apparent differences between 7lattice and 50lattice. Although 7lattice terrain might be less representative of the exact topography than the 50lattice, it was considered to be a sufficient source for the study purposes. Additionally, since 7lattice terrain takes less analysis time than 50 lattice terrain, viewshed delineation, was based on the 7lattice terrain

Viewshed delineation, the third step defined the visible area for each sampled viewpoint. Five factors affected the extent of the viewshed as follows:

1. Elevation of the viewpoint in general: The higher the elevation, the farther the viewer can see and the greater the total area seen.
2. Height of the observer: was set at 1.75 meters a height consistent with the eye level of the average viewer.
3. The viewing angle: The natural vertical view angle of the human being is 14 (in both upward and downward directions) degrees when the viewer keep his/her head in normal position. To set viewing angle of 14 degrees can avoid redundant spatial analysis of GIS.

4. Viewing distance. Viewing distance affects the appearance of physical features. Although weather conditions affect the maximum viewing distance, but it is not manageable. Since all of the pictures were taken on sunny days, it was assumed that the farthest distance the naked eyes can see is 40km. Viewing distance, then, was split into three zones, foreground (0-500m), middleground (500-4,400m), and background (4,400-40,000m).
5. The height of vegetation: The height of vegetation also affects the viewshed extent. Viewsheds were produced by the seen-area operated in ARC, using the elevation of the original (bare-earth) terrain, this bare-earth terrain plus the height of vegetation, which based on the GAP coverage.

Finally, each viewshed, defined as above, served as a "cookie cutter" to extract and quantify selected physical landscape variables within each viewshed (e.g., vegetation cover, topograpology, water features).

GIS Database Interpretation

The analysis results of ARC/INFO are too exact for the neural network to deal with effectively. The performance of neural network is better on grouped data than individual value. The physical variables were grouped into classes and their values were individually standardized to a 0 to 1 scale.

As result, the processed database should reduce the training time since neural network is able to identify the more restricted set of possible patterns easily.

Table 5 Interpolated distance zone (meters)

Foreground	0-500	3	0.3
Middleground	500-4400	6	0.6
Background	4400-40000	9	0.8

According to early definition, the distance was classified into three zones, foreground (0-500m), middleground (501-4,400m), and background (4,401-40,000m) and each zone was assigned a specific numerical value for input of neural network (Table 5).

Each viewshed was zoned on the basis of distance. The roughness of topography was defined as the elevation variation within a viewshed, the higher numerical value indicates greater variation within the viewshed (Table 6).

Table 6 Interpolated roughness of topography range (Standard Deviation)

0-4	0.1	1
5-10	0.2	2
11-20	0.3	3

21-40	0.4	4
41-60	0.5	5
61-80	0.6	6
81-100	0.7	7
101-150	0.8	8
151-200	0.9	9
201-500	1.0	10

Natural aspects were classified into nine categories, including north, northeast, east, southeast, south, southwest, west, northwest, and flat (zero slope). Increment increasing from the north travels in a clockwise direction. Each aspect covers a range of 45 degrees (Table 7).

There were two factors considered when classifying topography. Previous research (Iverson, 1975) has shown that humans begin to sense "steep" of the slopes in excess of 30 percent. Second, in order to incorporate with natural resource management in future studies, limitations involved in development were considered. That is, 0 to 3 percent of slope traditionally is considered the best range for facility construction and development, while slopes which exceed 30 percent of slope is unsuitable for development, as a consequence, slope was classified to the three classes, shown in Table 8, Table 9, and Table 10. They explain the meaning of each code in the Dixie National Forest data dictionary and associated numerical values for analysis purpose.

Table 7 Interpolated Natural Aspect Classification (degree)

Flat	-1	1	0.1
North	0 -22.5, 292.5 - 360	2	0.2
Northeast	22.5 - 67.5	3	0.3
East	67.5 - 112.5	4	0.4
Southeast	112.5 - 157.5	5	0.5
South	157.5 - 202.5	6	0.6
Southwest	202.5 247.5	7	0.7
West	247.5 292.5	8	0.8

Table 8 Interpolated Slope Range (%)

0 - 3	4	0.4
3 - 30	7	0.7
30 - 100	10	1.0

Table 9 Interpolated Values Associate Rivers' Types

Perennial Streams	402	2	0.2
Large Perennial Stream	403	4	0.4
Intermittent Stream	405	6	0.6
Large Intermittent Stream	406	8	0.8
Stream Disappearing at a definite point	407	10	1.0

Table 10 Interpolated Values Associated with Transportation

Layer

Scenic and Recreational trail	95	1	0.1
Secondary highway	103	2	0.2
Dirt improved road	105	3	0.3
Unimproved road	106	4	0.4
Trails	107	5	0.5
Paved improved road	517	6	0.7
Gravel improved road	518	7	0.7

Three categories of visible area were classified according to distance zones, see Table 11. Foreground was defined as the area within 0-500 meters of the observer. Middleground was seen between 501 and 4400 meters, and background was from 4401 to 40,000 meters. The larger the area the stronger effect on perception, owing to the size variation of area in each distance zone, so that the class ranges of each area depend on the largest area in each distance zone and the variety of areas, then, three areas were divided into 10 classes. (Table 11 and Table 12).

Table 11 Interpolated Total Visible Area at a View Point (Km^2)

0-1	1	0.1
1-2	2	0.2
2-3	3	0.3
3-4	4	0.4
4-5	5	0.5

5-6	6	0.6
6-9	7	0.7
9-12	8	0.8
12-15	9	0.9
15-50	10	1.0

Table 12 Interpolated Areas in Three Distance Zones (Km^2)

0-.0.5	0-1	1-2	1	0.1
0.5-1	2-3	2-3	2	0.2
1-1.5	3-10	3-10	3	0.3
1.5-2	10-20	10-20	4	0.4
2-2.5	20-30	20-30	5	0.5
2.5-3	30-50	30-50	6	0.6
3-3.5	50-80	50-80	7	0.7
3.5-4	80-110	80-110	8	0.8
4-8	110-200	110-200	9	0.9
8-16	200-500	200-500	10	1.0

[1]FG = Foreground Km^2
[2] MG = Middleground
[3] BG = Background

Elevation change affects the relationship between objects' position and observers. Relative elevation is the elevation of observer minus the average elevation of in each distance zone. That is, the difference between observer elevation and object elevation. For the vista studies, generally, the elevation of foreground was flatter than the elevation of the other two distance zones. As the point elevation increase, distance of view tends to increase. Similarly negative differences in elevation reduce the distance the observer can see. (Table 13

and 14).

Table 13 Interpolated Elevation of Total Visible Area within a Viewshed (m)

2300-2450	1	0.1
2450-2600	2	0.2
2600-2750	3	0.3
2750-2900	4	0.4
2900-3050	5	0.5
3050-3200	6	0.6
3200-3350	7	0.7
3350-3500	8	0.8
3500-3650	9	0.9
3650-3800	10	1.0

Table 14 Interpolated Relative Elevation within Three Distance Zones (m)

-150~-100	-300~-240	-500~-400	1	0.1
-100~-50	-240~-180	-400~-300	2	0.2
-50~-30	-180~-120	-200~-100	3	0.3
-30~-20	-120~-60	-100~0	4	0.4
-20~-10	-60~0	0~100	5	0.5
-10~-5	0~50	100~200	6	0.6
-5~0	50~100	200~300	7	0.7
0~5	100~150	300~400	8	0.8
5~10	150~200	400~500	9	0.9
10~20	200~250	500~600	10	1.0

[1]FG = Foreground
[2] MG = Midground
[3] BG = Background

Table 15 Interpolated Classes of Dominant Vegetation Area

(Km^2)

0-10000	1	0.1
10000-50000	2	0.2
50000-100000	3	0.3
100000-500000	4	0.4
500000-2000000	5	0.5
2000000-3000000	7	0.7
3000000-4000000	9	0.9

Table 15 illustrates the classes of area size of the dominant vegetation type. Table 16 shows the meaning of codes associated with each vegetation type in National Forest data dictionary, and the assigned numerical values for input to the neural network estimation model.

Table 16 Classifications and GIS Values Associated with Vegetation Types

1	4	0.04	Water
2	8	0.08	Spruce-Fir
3	12	0.12	Ponderosa Pine
5	16	0.16	Mountain Fir
7	20	0.20	Pinyon
9	24	0.24	Mountain Mahogany
10	28	0.28	Aspen
11	32	0.32	Oak
13	36	0.36	Mountain Shrub
14	40	0.40	Sagebrush
15	44	0.44	Sagebrush
16	48	0.48	Sagebrush/Perennial Grass
17	52	0.52	Grassland
18	56	0.56	Alpine
19	60	0.60	Dry Meadow

20	64	0.64	Wet Meadow
22	68	0.68	Barren
23	72	0.72	Ponderosa Pine/Mountain Shrub
24	76	0.76	Spruce-Fir/ Mountain Shrub
25	80	0.80	Aspen/Conifer
26	84	0.84	Mountain Riparian
29	88	0.88	Lava
30	92	0.92	Agriculture
31	96	0.96	Urban

3.3 Neural Net Modeling

A neural net-based Vista SBE model was developed for two purposes. First to identify GIS predictor variables. Second to associate these physical variables with SBE ratings' to predict SBE on a user basis. At present, there are many neural network control strategies and architectures that have been developed. One of the most famous and the most successful neural network is the back-propagation model that was developed by Rumelhart et al. (1986). The Back-propagation model was chosen in this study to illustrate how the neural computing technology can be integrated with GIS modeling and used to predict scenic beauty.

This neural-net based Vista SBE model includes two neural networks; NN1 and NN2 (Figure 10). The function of the first neural network, NN1, was to interpolate scenic preferences. It can be taught to recognize and classify patterns found within input data (perfect training samples) and desired

output values (scenic beauty ratings). The function of the second neural network, NN2, was to predict scenic preference for vistas based on their physical features. Both networks were created with a typical a three-layer structure using back-propagation neural network. In NN1, the input node number depends on the number of observations for each vista. There are 13 subjects in this study. Thus NN1 has 13 nodes in the input layer. NN1 was assigned 5 nodes in the hidden layer, with 10 nodes in the output layer, corresponding to the scenic rating scale (0 - 9). NN2 has 43 nodes in the input layer, representing the selected physical landscape variables. The desired output of NN2 was the interpolated scenic beauty judgments (5 nodes) of NN1. Several different structures of NN2 were tested by changing the number of nodes in the hidden layer (from 80, to 30, to 10, to 5 nodes) in order to find the network which had the best performance ability. The changes didn't degrade the performance of network. In other words, 5 nodes in the hidden layer nodes were sufficient for SBE modeling. Neural networks are trained on a file structured as input data patterns and their corresponding output patterns. The desired output patterns represent the meaning of the application, so that the input data can be translated to a meaningful form.

Back-propagation networks, a calculus based method, was chosen because it is a very powerful technique for constructing non-linear transfer functions between several

continuous valued inputs and one or more continuously valued outputs (Neural Computing, 1991). There is no theoretical limit on the number of hidden layers but typically there will be one or two. Some work has been done which indicates that a maximum of four layers (three hidden plus one output layer) are sufficient to solve most problems.

The internal weights used by the network in the comparison algorithm were set to .1 for both nets. The networks adopted a sigmoid transfer function, a summation function with learning rates at 0.9, a momentum term of 0.6, epoch 7. During learning, errors is propagated back through the network and used to update the connection weights. In order to determine which processing element and inter-connection should be adjusted, back-propagation assumes that all processing elements and connections transfer errors.

Figure 9 The Concept of Neural Networks - the Structure and Associated Mappable Physical Variables and The Relationships With Stimuli.

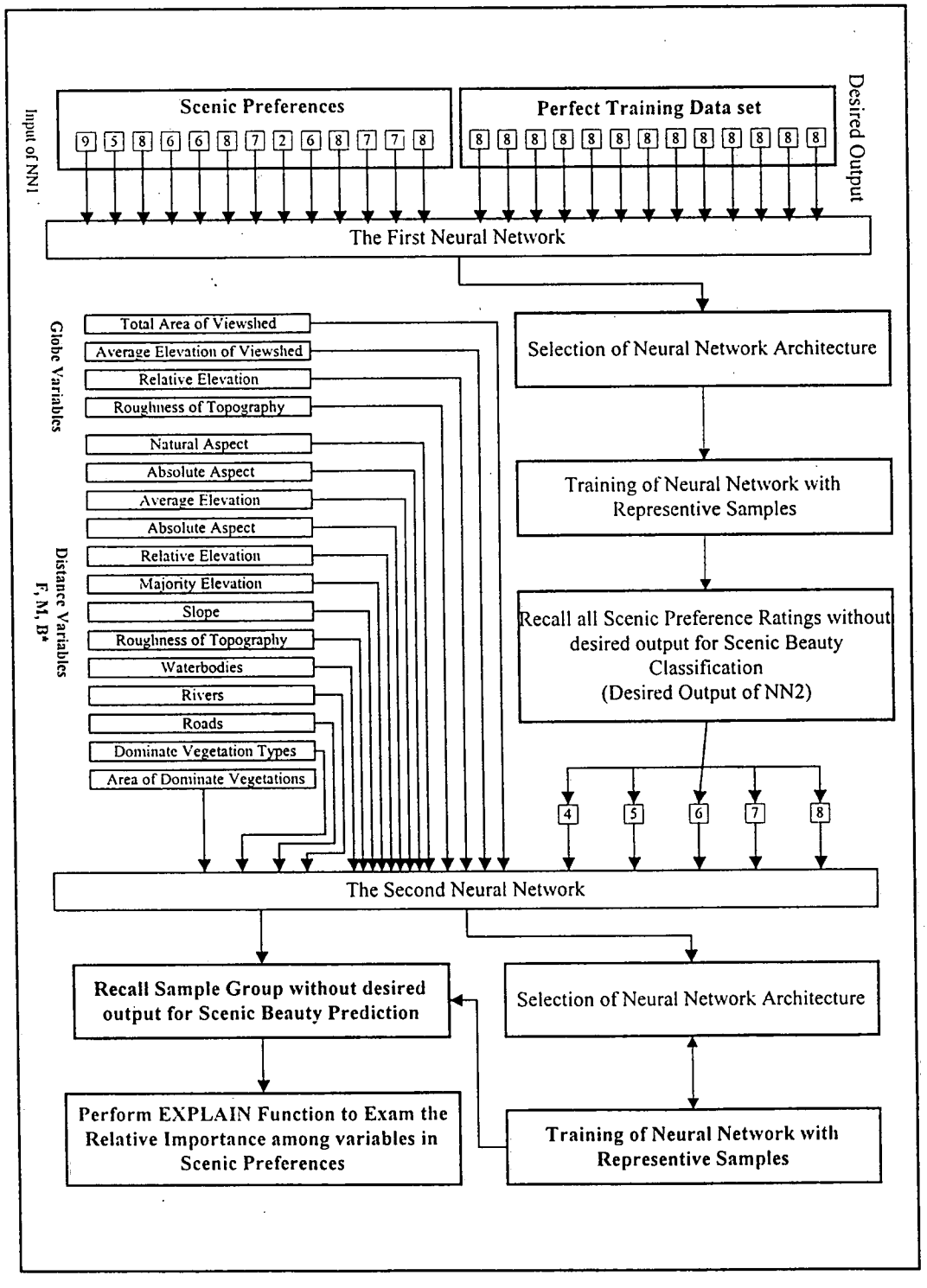

Input of NN1
Scenic Preferences
9 5 8 6 6 8 7 2 6 8 7 7 8
Perfect Training Data set
8 8 8 8 8 8 8 8 8 8 8 8 8
Desired Output
The First Neural Network
Selection of Neural Network Architecture
Training of Neural Network with Representive Samples
Recall all Scenic Preference Ratings without desired output for Scenic Beauty Classification (Desired Output of NN2)
Globe Variables
Total Area of Viewshed
Average Elevation of Viewshed
Relative Elevation
Roughness of Topography
Distance Variables F, M, B*
Natural Aspect
Absolute Aspect
Average Elevation
Absolute Aspect
Relative Elevation
Majority Elevation
Slope
Roughness of Topography
Waterbodies
Rivers
Roads
Dominate Vegetation Types
Area of Dominate Vegetations
4 5 6 7 8
The Second Neural Network
Recall Sample Group without desired output for Scenic Beauty Prediction
Selection of Neural Network Architecture
Perform EXPLAIN Function to Exam the Relative Importance among variables in Scenic Preferences
Training of Neural Network with Representive Samples

Table 17 The Explanations and Functions of Essential Parameters Used in the Back-propagation Neural Network.

Control Strategy	To specify the order in which network states are updated for digital implementation of complicated learning and recall functions.
Learning	Self-adaptation at the processing element level. Weighted connections between processing element are adjusted to achieve specified results, and eliminating the need for writing a specific algorithm for each problem.
Learning Schedule	A schedule which specifies how parameters associated with learning change over the course of training a network.
Transfer Function	The component of a processing element through which the sum is passed (transformed) to create net output. "Locally" linear is defined by the size of the learning coefficient.
Momentum	It effects learning coefficient, a smaller learning coefficient cause a slower learning speed. One the other hand, a bigger coefficient may cause divergent behavior occur near a t the points of high curvature. That is, it affects the detecting of global errors.
Epoch	An epoch is the number of training presentations between weight updates. It is a cumulating cycle, for example, there are 13 input in this study, it is better to set epoch to 13 so that a whole set of data (values of 13 variables) can be processed at the same cycle.

Table 17 provides a brief explanation of the essential parameters in a back-propagation neural network. Training continually attempts to correct and improve its performance by propagating the output error backward through the node connections to the previous layer. Training continues until

no further improvement in performance is made or the network converges to some desired level. Once learning has occurred, then, the entire data sets can be recalled through the net for optimize classification. The data sets that are recalled structured in exactly the same way as the training files, except they do not include the desired outputs. A neural network is capable of recognizing patterns in similar data if it is well trained, so that during the recall procedure, the neural network will be able to associate patterns among physical variables with predicted scenic beauty ratings. Only one node in the output layer (scenic beauty ratings) could be activated when a pattern of physical variables (a vista) is associated with one of scenic beauty classes. The value of this output node will be much bigger than the values of other nodes in the output layer. The reason only one node can be activated is due to the characteristics of back-propagation. Thus, it couldn't happen that a viewpoint is assigned several scenic beauty ratings.

4 APPLICATION OF METHODS AND RESULTS

This chapter describes the application of the research method outlined in Chapter 3.0 and presents the results of the neural net-based vista scenic beauty modeling in forest landscape settings.

4.1 Experiment Procedure

Thirteen subjects were tested and their responses were recorded to Vista Scenic Beauty Estimation procedures during May 1995. The subjects came from a variety of majors (landscape architecture, architecture, physics, electric engineering, renewable natural resources, and wildlife science) and nationalities (Mainland China, Greece, Taiwan, America, Mexico, Canada, France, and Japan), but all of them were students at University of Arizona.

An oral explanation accompanied by a written introduction was provided to each respondent explaining the research purpose and methods for the experiment. A set of "preview" images showed representative views that were to be preseented to the subjects. The preview images were individual scenes ("40") chosen from four directions roughly 90 degrees apart in each panoramic view. The purpose of showing preview images was to provide context for the subjects and to establish the

use the 10-point scenic beauty rating scale to rate the panoramas in the experiment.

Each site was represented by a 360-degree panorama presented on a 17" high-resolution computer screen. Approximately hundred percent of the panorama was visible at any time, and subjects were able to look at any segment of the panorama as long as they wish by using the right and left arrow keys on the keyboard to view different parts of the panoramas. The North segment of each panorama was always presented first. A small "compass" appeared in the lower right corner of the screen to indicate which segment direction of the panorama was being presented. Subjects looked through the whole panorama, and when they were ready to rate the panorama, they pressed the Escape key and a screen appeared asking the subjects to enter their rating (0-9) by pressing the appropriate number key. The ratings were based on the whole panoramic view. The next panorama was displayed after the subjects indicated their scenic beauty rating. The subjects continued this procedure until they had rated all 21 panoramas for the study site.

Once subjects finished rating the forest vista panoramas, they were asked to recall and list the positive and the negative landscape features that affected their scenic beauty ratings. A list of typical forest landscape features was provided for assistance.

4.2 Description of the Data Set

The sample size of this study is smaller than desired. None these observer-to-observer and group-to-group reliability coefficients were calculated. The observer to observer coefficient was considered low (0.33) compared with previous research (range from 0.75 to 0.91, Buhyoff at al, 1982), but the group to group reliability was considered sufficient at 0.865. According to previous research (Hull & Buhyoff, 1981) group related coefficients usually range from 0.86 to 0.95. Since this study focused on group opinion, and did not intend to distinguish among individual observers' differences, the obtained group to group reliability was deemed acceptable for this pilot study.

Original SBE scores is listing in Table 18, which was collected from the laboratory experiment. The original SBE score was used as the recall data set for NN1, and NN1 was trained on a perfect training set (Table 19). The desired output patterns direct which specific node will be activated, representing the SBE rating. The learning result of NN1 is shown in Table 20. The original SBE scored can be adjusted to an, theoretically speaking, unbiased SBE scores.

The SBE Rating scale is an ordinal, strictly speaking, scale; that is higher ratings individual with higher preferences, but the magnitude of the difference in preferences may not be responded to the magnitude of the

difference in ratings. That is, more highly visual-pleasing scenes will always get relatively higher SBE ratings. To prove this point, the original SBE rating scores was transformed by using RMRATE. RMRATE transformed the original ratings into an interval scale index of preference for each scene. Table 20 and figure 11 present the relationships among 1) the results of NN1, 2) the mean of original rating scores, and 3) the SBE index. These scales were all highly correlated, mediating that each provides an equivalent measure of scenic preference. The reclassified scenic scores of each vista panorama from NN1 were used as the training set outputs for NN2.

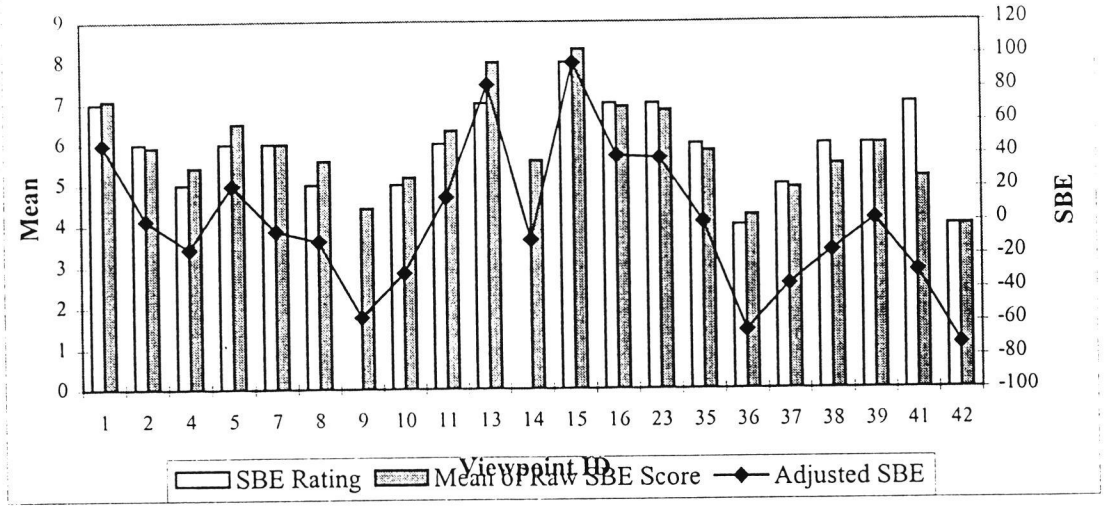


Figure 10 Figure 11 The Relationships Among Mean, SBE, and

Table 18 Original SBE scores that were derived from participants.

| | | |

Table 19 The Perfect Training Set - Scores for The First NN.

10	9	8	7	6	5	4	3	2	1	13	12	11	10	9	8	7	6	5	4	3	2	1
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	1	0	0	2	2	2	2	2	2	2	2	2	2	2	2	2
0	0	0	0	0	0	1	0	0	0	3	3	3	3	3	3	3	3	3	3	3	3	3
0	0	0	0	0	1	0	0	0	0	4	4	4	4	4	4	4	4	4	4	4	4	4
0	0	0	0	1	0	0	0	0	0	5	5	5	5	5	5	5	5	5	5	5	5	5
0	0	0	1	0	0	0	0	0	0	6	6	6	6	6	6	6	6	6	6	6	6	6
0	0	1	0	0	0	0	0	0	0	7	7	7	7	7	7	7	7	7	7	7	7	7
0	1	0	0	0	0	0	0	0	0	8	8	8	8	8	8	8	8	8	8	8	8	8
1	0	0	0	0	0	0	0	0	0	9	9	9	9	9	9	9	9	9	9	9	9	9

1: Activated Node
0: No-activated Node

Table 20 The Learning Result of NN1 and The Relationships Among the Mean of Raw Score, SBE and Reclassified SBE by NN1.

1	7	7.08	46.31	.587933
2	6	5.92	0.76	.610763
4	5	5.42	-15.93	.63344
5	6	6.5	21.69	.673072
7	6	6	-5.51	.626352
8	5	5.58	-11.41	.588892
9	5	4.42	-56.69	.640936
10	5	5.17	-30.14	.675274
11	6	6.33	14.55	.652842
13	7	8	82.35	.401748
14	5	5.58	-10.59	.567157
15	8	8.33	95.38	.327538
16	7	6.92	39.38	.59128
23	7	6.83	38.1	.610365
35	6	5.83	-0.11	.568568
36	4	4.25	-64.73	.651621
37	5	4.92	-36.98	.669634
38	6	5.5	-17.22	.564301
39	6	6	1.63	.656078
41	7	5.17	-29.51	.655634
42	4	4	-72.94	.64989

4.3 Modeling Results

The vista scenic beauty prediction is based on the identified physical features (as inputs) for each viewpoint, as manipulated by GIS. Thus, the structure of the training set for NN2 consisted of GIS-based prediction variables (input)

corresponding with their classified (NN1) scenic ratings for each vista. The training set of NN2 is shown on Table 21 and table 22. There were 21 viewpoints for which GIS databases were generated. They were randomly split into two groups, experimental group and reference group, for experimental purpose. Experimental group contained the GIS database of 16 panoramas and was used as the NN2 training set. The NN2, then, was trained on only the 16 randomly selected sample GIS database of 16 panoramas. The reference group contained GIS database of 5 panorama and was used as a recall set in order to test the reliability of the trained neural network for predicting scenic scores for panoramas not in the training set. The structure of recall set is similar as the training set, but it is without the corresponding outputs.

Additionally, the number of samples restricted the structure of the neural net and it's accuracy. In general, the more samples in the training set the greater accuracy of the result. The number of samples (panoramas) must exceed the number of physical landscape variables (inputs), or the capacity of neural net cannot be satisfied.

Five viewpoints were recalled, 1, 7, 15, 23, 38. Table 23 shows the scenic beauty predictions of NN2 after recall. The predictions perfectly matched the NN1 classified preference rating score. For example, viewpoint 1 has a scenic score of 7 and the appropriate node, 4, was activated in recall. The output value of each activated node is much higher than the

rest of nodes. In other words, by providing enough ground information (physical features) for the inputs of a NN1/NN2, both nets were able to recognize different patterns of forest settings and to assign correct scenic class to panoramas that are not in the training set. Two possible reasons might explain this phenomena. First, the selected input variables are the most representative ones and they have great influence on vista scenic preference. Second, the patterns presented to the NN from the training data set is quite easy to be recognized. That is, the neural network has the ability to assess more complex relationships between physical variables and scenic beauty preferences at the vista scenic beauty modeling.

In order to explore the influence and relatively magnitude of each predictor variable, the EXPLAIN function, which built in Professional NeuralWork II was implored. The EXPLAIN function analyzed the contribution of each input variable across the tested panoramas and it provides a means for explaining contribution of each variables to the prediction outcome. Tables 22 lists the output value generated by the EXPLAIN function for the recall panoramas, 1, 7, 15, 23, and 38 with their predicted scenic classes 7, 5, 8, 4, 6.

Table 21 The Input Value of Predict Variables in Training Set.

PT	TA	TME	TRE	TR	FAA	FNA	FA	FE	FRE	FMJ	FSLP	FR	FW	FR	FRD	FV	FVA	MAA	MNA	MA	ME	MRE
1	0.1	0.5	0.6	0.1	0.8	0.5	0.7	0.4	0.7	0.08	0.24	0.2	0.7	0.4	1	1	1	0.2	0.4	0.6	0.5	0.95
2	0.1	0.5	0.6	0.1	0.5	0.5	0.5	0.3	0.5	0.08	0.9	0.2	0.7	0.3	0	1	1	0.2	0.4	0.5	0.5	0.7
4	0.3	0.5	0.6	0.2	0.8	0.5	0.7	0.4	0.7	0.44	0.15	0.4	0.1	0.2	0	1	1	0.5	0.4	0.6	0.5	0.45
5	0.1	0.4	0.6	0.2	0.4	0.5	0.9	0.3	0.7	0.56	0.67	0.6	0.7	0.3	0	0	1	0.3	0.4	0.5	0.5	0.1
7	0.3	0.5	0.6	0.1	0.6	0.5	0.5	0.4	1	0.08	0.25	0.4	0.7	0.3	0	0	0	0.4	0.4	0.5	0.5	0.7
8	0.5	0.6	0.5	0.3	0.5	0.6	0.3	0.6	1	0.64	0.87	0.6	0.4	0.3	0	1	0	0.6	0.6	0.5	0.8	0.65
9	0.4	0.6	0.5	0.3	0.3	0.8	0.5	0.7	1	0.64	0.16	0.5	0.4	0.3	0	1	1	0.5	0.7	0.4	0.9	0.6
10	0.5	0.6	0.4	0.4	0.6	0.9	0.8	0.7	1	0.64	0.68	0.7	0.7	0.4	0	1	1	0.4	0.8	0.4	0.9	0.6
11	1	0.6	0.2	0.6	0.4	0.9	0.3	0.7	1	0.64	0.65	0.4	0.7	0.7	0	1	1	0.7	0.8	0.3	0.9	0.55
13	1	0.6	0.1	0.6	0.1	0.9	0.3	0.8	1	0.64	0.19	0.7	0.7	0.4	0	0	0	0.8	0.7	0.1	0.9	0.41
14	0.2	0.8	0.6	0.1	0.6	0.9	0.7	0.7	1	0.64	0.55	0.3	0.4	0.2	0	0	1	0.4	0.9	0.5	1	0.95
15	0.3	0.6	0.7	0.3	0.9	0.6	0.8	0.5	0.2	0.64	0.13	0.4	0.4	0.2	1	1	1	0.8	0.7	0.7	0.9	0.1
16	0.2	0.6	0.5	0.6	0.4	0.8	0.9	0.6	0.7	0.64	0.78	0.7	0.7	0.3	0	0	1	0.2	0.8	0.6	0.9	0.6
23	0.2	0.7	0.6	0.1	0.4	0.8	0.7	0.6	0.9	0.64	0.67	0.6	0.7	0.3	0	1	1	0.1	0.8	0.5	0.9	0.4
35	0.4	0.4	0.9	0.6	0.2	0.2	0.6	0.2	0.35	0.56	0.24	0.3	0.7	0.7	0	1	1	0.7	0.4	0.9	0.5	0.65
36	0.7	0.4	0.8	0.9	0.6	0.2	0.4	0.1	0.3	0.84	0.9	0.2	0.7	0.5	0	1	1	0.8	0.4	0.9	0.3	0.5
37	0.4	0.4	0.9	0.9	0.2	0.2	0.9	0.1	0.35	0.44	0.13	0.2	0.7	0.4	0	1	1	0.3	0.4	1	0.6	0.7
38	0.5	0.4	0.9	0.6	0.7	0.1	0.8	0.1	0.3	0.4	0.35	0.4	0.7	0.5	0	1	1	0.7	0.3	0.9	0.1	1
39	1	0.3	0.6	0.9	0.1	0.2	0.1	0.1	0.9	0.08	0.79	0.8	0.7	0.2	0	1	0	0.1	0.2	0.4	0.1	0.3
41	0.2	0.5	0.8	0.5	0.4	0.5	0.6	0.4	0.65	0.56	0.83	0.2	0.4	0.2	1	1	1	0.4	0.6	0.8	0.5	0.9
42	0.5	0.5	0.9	0.5	0.8	0.4	0.6	0.3	0.45	0.44	0.34	0.3	0.4	0.2	1	1	1	0.6	0.5	0.7	0.5	0.1

TA Total area of each veiwshed

TAE Average elevation of each viewshed

TRE Observer's elevation minus average elevation of eacl

TR Roughness

*AA Actural aspect in foreground

*NA Natural aspect in forrground

*A Area in fourground

*E Average elevation in foreground

*MJ Major elevation in foreground

*SLI Average slope in foreground

*R Roughness in foreground

*W Waterbody in foreground

*R Rivers in foreground

*RD Roads in foreground

Table 22 The Input Value of Predict Variable in Training Set.

PT	MMJ	MSLP	MR	MW	MR	MRD	MV	MVA	BAA	BNA	BA	BE	BRE	BMJ	BSLP	BR	BW	BR	BRD	BV	BVA
1	0.08	0.34	0.3	0.7	0.7	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0.08	0.23	0.2	0.7	0.7	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0.08	0.23	0.3	0.7	0.7	0	1	1	0.1	0.7	0.6	1	0.45	0.12	0.24	0.3	0.7	0.7	0	0	1
5	0.56	0.67	0.6	0.7	0.3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0.08	0.14	0.3	0.4	0.5	0	0	1	0.2	0.6	0.5	0.9	0.85	0.08	0.14	0.3	0.7	0.6	0	1	1
8	0.64	0.83	0.2	0.7	0.5	0	1	1	0.2	0.6	0.3	1	0.85	0.08	0.73	0.9	0.7	0.7	0	1	1
9	0.12	0.83	0.2	0.7	0.5	0	1	1	0.2	0.7	0.3	1	0.4	0.12	0.2	0.9	0.7	0.8	0	1	1
10	0.64	0.68	0.7	0.7	0.4	0	1	1	0.2	0.7	0.2	1	0.1	0.12	0.14	0.3	0.7	0.8	0	0	1
11	0.64	0.65	0.4	0.7	0.7	0	1	1	0.6	0.6	0.1	1	0.55	0.08	0.83	0.2	0.7	0.9	1	1	1
13	0.64	0.83	0.2	0.7	0.8	1	1	1	0.6	0.6	0.1	1	0.6	0.08	0.83	0.2	0.7	0.9	1	1	1
14	0.64	0.55	0.3	0.4	0.2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0.08	0.24	0.4	0.7	0.8	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0.64	0.78	0.7	0.7	0.3	0	0	1	0.2	0.6	0.3	0.7	0.95	0.08	0.83	0.2	0.7	0.8	0	0	1
23	0.64	0.56	0.5	0.7	0.7	0	0	1	0.2	0.7	0.4	1	0.85	0.12	0.68	0.7	0.7	0.6	0	0	0
35	0.08	0.24	0.3	0.7	0.9	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0.08	0.24	0.3	0.7	0.9	0	1	1	0.4	0.1	0.4	0.1	0.1	0.68	0.72	0.1	0.4	0.6	1	0	1
37	0.08	0.24	0.2	1	0.9	0	1	1	0.2	0.1	0.4	0.1	0.45	0.68	0.73	0.2	0.7	0.6	0	0	1
38	0.08	0.24	0.3	0.7	0.9	1	1	1	0.3	0.5	0.6	0.6	0.85	0.08	0.23	0.3	0.7	0.7	0	0	1
39	0.08	0.24	0.3	0.7	0.8	1	1	1	0.6	0.3	0.5	0.1	0.35	0.08	0.14	0.3	0.7	0.9	1	1	1
41	0.08	0.13	0.2	0.7	0.9	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
42	0.56	0.47	0.4	0.7	0.8	1	1	1	0.3	0.7	0.6	1	0.7	0.08	0.34	0.3	0.7	0.9	0	0	0

*V Vegetation types in foregournd

*VA Vegetation area for each species in foreground

F Foreground

M Middleground

B Background

* All of the variables are the same sequency in fore, middle, and background
Add F, M and B frond of each variables.

Note that the total area of the viewshed had more effect on the scenic class of viewpoint 15 than for viewpoint 23. Viewpoint 15 has the larger area and the higher scenic score, while viewpoint 23 has the smaller area and the lower scenic score. Figure 12, Figure 13, Figure 14 and Figure 15 illustrate the relationships among input variables across the five test viewpoints.

Table 23 The Scenic Score for Each Activated Node (A), and The Prediction Result of NN2 (B).

A: Training Set of NN2					
SBE Rating	4	5	6	7	8
Activated Node	1	0	0	0	0
	0	1	0	0	0
	0	0	1	0	0
	0	0	0	1	0
	0	0	0	0	1

B: Prediction Result of NN2			
Test Point	SBE Rating	Actovated Node	The Output value of Activated Node
1	7.0	4	0.994973
7	5.0	2	1.003922
15	8.0	5	0.997066
23	4.0	1	1.000202
38	6.0	3	0.997014

The effect of the prediction variables used in the neural network can be interpreted similar to the variable weights in multiple regression models. According the result of EXPLAIN, the prediction variables, waterbody in foreground, relative elevation of total area in viewshed, the area of viewshed, the variety of vegetation types in both the middle and the back

ground, all had positive effects on scenic preference. The predictor variables, average elevation within viewshed and roads in foreground had the opposite tendency.

4.4 Discussions

What does a viewpoint with vista scenic beauty estimation (VSBE) value of 7 mean? What does higher VSBE value reflect to physical features? Merely knowing that a viewpoint has VSBE value of 7 is not enough. Do those physical variables are suitable for representing forest settings? What physical features are more important than other in terms of estimating scenic beauty? What are the relationships among those physical variables? Does neural network model classify and predict scenic beauty as expected other than recognize other geographical patterns? The neural net-based vista scenic beauty models provide some insights into the nature of vista-view in forest settings.

Interpretation of Physical Variables

A VSBE value is the result of different combinations of physical features. Apparently watebody, road, vegetation area, vegetation type, slop, and relative elevation are the most distinctive variables. They have higher relative importance in each scene and they have different magnitude in each distance zone. For example, High scenic beauty may occur where

waterbody (ponds and lacks) or rivers (stream and washes) is presented (viewpoint 15), or hilly landform (viewpoint 32), smoothly landform change (viewpoint 1), and variety of vegetation (viewpoint 6). On the other hand, low scenic beauty may occur where roads present (viewpoint 36), or flat landform with vegetation blocked view (viewpoint 23), or viewpoint with relative low elevation that limited viewing distance (viewpoint 7).

Figure 12, 13, 14, and 15 indicate the relative importance and magnitude among each variable according to different distance zone. Each selected variable can be compared by individual viewpoint, or compare across viewpoints.

1. Visible area: The bigger the total visible area doesn't mean the higher the vista SBE value. It is relatively important in affecting the SBE value of viewpoint 15, but not important in that of viewpoint 1, 7, 23, 28. Three variables ▒ relative elevation in middleground and vegetation area in middleground, and the variety of vegetation in the background should be considered because of their interrelationships.
2. Aspect: The results suggest that aspects have higher magnitude in middleground and background, especially absolute aspect. Absolute aspect is aspect relative to the observer. The more directly a face of an object is turned toward a viewer, the larger it will

appear. (Iverson, 1985) That is, absolute aspect determines whether an observer can perceive objects or not, and how much amount of objects observer can see. Viewpoints 15 and 38 have higher SBE value with higher percentage of absolute aspect within visible area. Results also suggest that aspects may interrelate with the variety of vegetation.

3. Elevation: Several approaches for analyzing elevation were used- relative elevation, average elevation, and elevation of viewpoint. Only relative elevation will be necessarily used in vista SBE model. According to the responses of participants, high viewing location is preferred. But elevation is relatively speaking, a viewpoint has high elevation doesn't necessary has better view. Thus, other two types of elevation are considered as redundant physical variables.
4. Distance: Distance ▒ weights▒ variables differently. The further away objects from the observer, the larger it must be to give the same amount of impression compared to close objects. Detailed physical features can't be seen when they are far away form observers, such as roads and rivers. Results suggest that the variety of vegetation and the coverage of vegetation area in both of middleground and background are important (viewpoints 7 and 15), while ground with the less coverage of

vegetation and the less variety of vegetation has lower landscape preferences (viewpoint 23). This finding strongly suggest that different variables should be considered to be used in different distance zones.

5. Slope and roughness: There are three possible effects are suggested according to the results, because people can only sense the changes of slope and roughness within foreground area. (1) Slope has higher magnitude in foreground area, because the steeper the slope, the more ▒ seen area▒ will be revealed (Iverson, 1985; Shafer, 1977). (2) Slope and roughness may be interrelated, that is, the smooth the slope, the less roughness of landform is. Participants indicated that rolling hills are preferred, while steep slopes and abrupt elevation changes are not, cliffs and canyons are exceptions.
6. Waterbody and river: Of the physical variables measured for this study, waterbody and river have by far the largest effect on scenic beauty and the greatest positive effect on scenic beauty in any size. This has obvious indication for scenic management. Any viewpoint that allows observer viewing waterbody or river, they deserve special consideration. The area that Waterbody locates required careful management.

7. Road: Roads have significant effect on scenic beauty according to this study. Participants also mentioned that artificial structures also have the same effects, because those scenes mean to be natural. Other landscape variables, such as power lines, campers or motor homes, fences, and signs should be considered in the future research.
8. Vegetation: A diversity of vegetation patterns and the coverage of vegetation have higher magnitude in middleground and background area.

Precision and accuracy of data

The ease of measuring landscape features and those physical features that are manageable are important in scenic beauty management. The accuracy and precision of geographical data are also important issues. Moffatt (1990) indicates that data retrial and analysis are affected by the degree of representing on-ground condition and accuracy of geographical data. For example, terrain model was driven from digital elevation model (DEM), it is easily updated to reflect wider range of landscape changes. The quality of vegetation data depends on the remote sensor platforms (Landsat satellite, TM, Spot, etc.). How much precision is needed to store and analyze scenic landscape information? On one hand, the finer data (e.g. remote sense, digital maps, etc.) take more effort to process and collect them. On the other hand, physical

attributes that are most readily measurable and most easily obtained from spatial data banks are not necessarily the most useful.

The representation of viewpoints

The present study is limited by the relatively small number of vistas, so the external validity and generality of the obtained neural net-based Vista SBE model cannot be assumed. However, this pilot model does show considerable potential for the incorporation of neural network techniques with SBE model to analyze vista scenic beauty.

Several problems were encountered that might have obscured the relationship between scenic preferences and physical landscape variables. First, a panoramic view consists of a number of scenes (segments), which may differ in their scenically relevant characteristics, causing conflicts and confusions when subjects try to overall scenic evaluations. Thus, each panorama may produce a "mixed-preference" reflecting the combination of differing scenic preferences for segments within the panorama.

It is important that the ground-based information in the GIS database and the photo-plane image are precisely matched together. What subject perceives from the 2-D images must be constantly and accurately related to the 3-D ground information. There are two ways to facilitate this. One is that the locations of each viewpoint should precisely geo-

referenced record by using GPS (global positioning system). Second the highest possible resolution should be maintained for the basic terrain and vegetation cover data.

Neural network

The main advantage of using neural networks (NN) is the possibility to analyze non-linear relationships. Cohen and Cohen (1975) stated ▒▒it is a fundamental law of psychophysics that constant increase in the size of a physical stimulus are not associated with constant increases in subjective sensation.▒ Previous research (Guiford, 1954; Steven, 1975; Buyhoff and Wellman, 1980) suggests the nonlinear relationship existing between scenic preferences and physical variables. The performance NN may be better than to the linear regression approach in terms of scenic beauty predictions and analyses, because NN allows better predictions of noise pollution levels than any other empirical relationship. Also it allowed to accounts for a large number of parameters (input), without particular computational problems.

Future research must focus on the continuing validation of these visual preference models, especially with regard to their predictive abilities. Further studies are needed, such as one reported by Itami (1994) and Bishop et al. (1995), to compare the prediction ability of traditional regression models and models based neural network techniques. Successful

vista scenic beauty models can be incorporated with other environmental data and model, including recreational opportunity, ecological and tourism models, allowing resource management agencies to make resource management decisions and actions efficient and accurately.

The strength and limitation of representation technique

This study introduced a new vista presentation technique named PANA, a computer presentation system, allowing interactive exploration of a full 360° view for scenic preference assessment. A primary of advantage to 360 computer-represented panorama is that it keeps the realism of photographic quality. Although images are fast to produce, while they take tremendous time to manipulate them.

Limitations to computer-represented panorama relate to the poor presentation speeds, at least for this pilot experiment. The "real world" sightseeing was not fully recreated. Additionally, it only creates a rotate movement, not forward movement.

The results of this study strongly encourage further efforts to develop neural net-based vista SBE models based on direct and GIS related measures of biophysical landscape variables.

Figure 11 Globe Variables for Selected Test Viewpoints

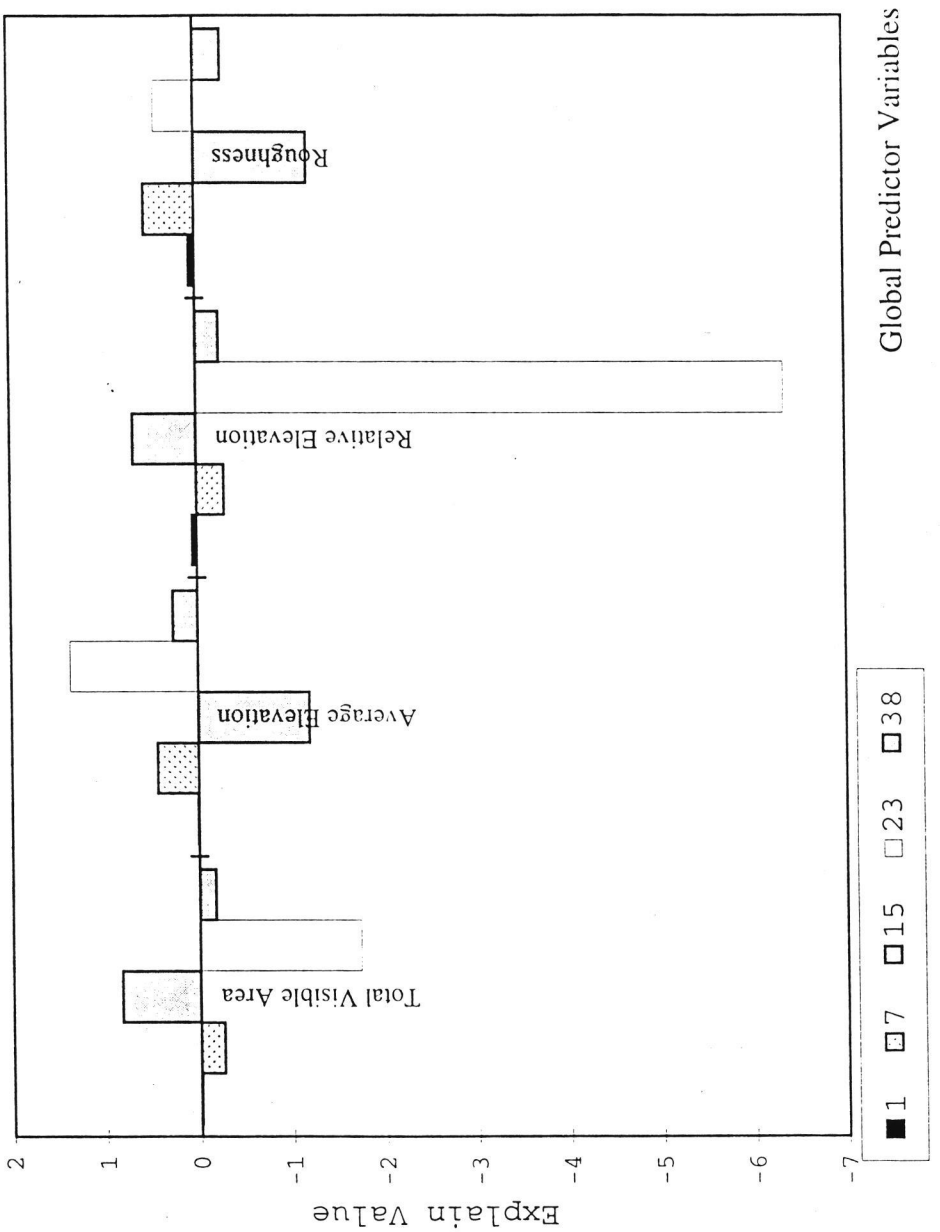


Figure 12 The Relative Importance of Foreground Predictor Variables Contribute on The Scenic Beauty Value

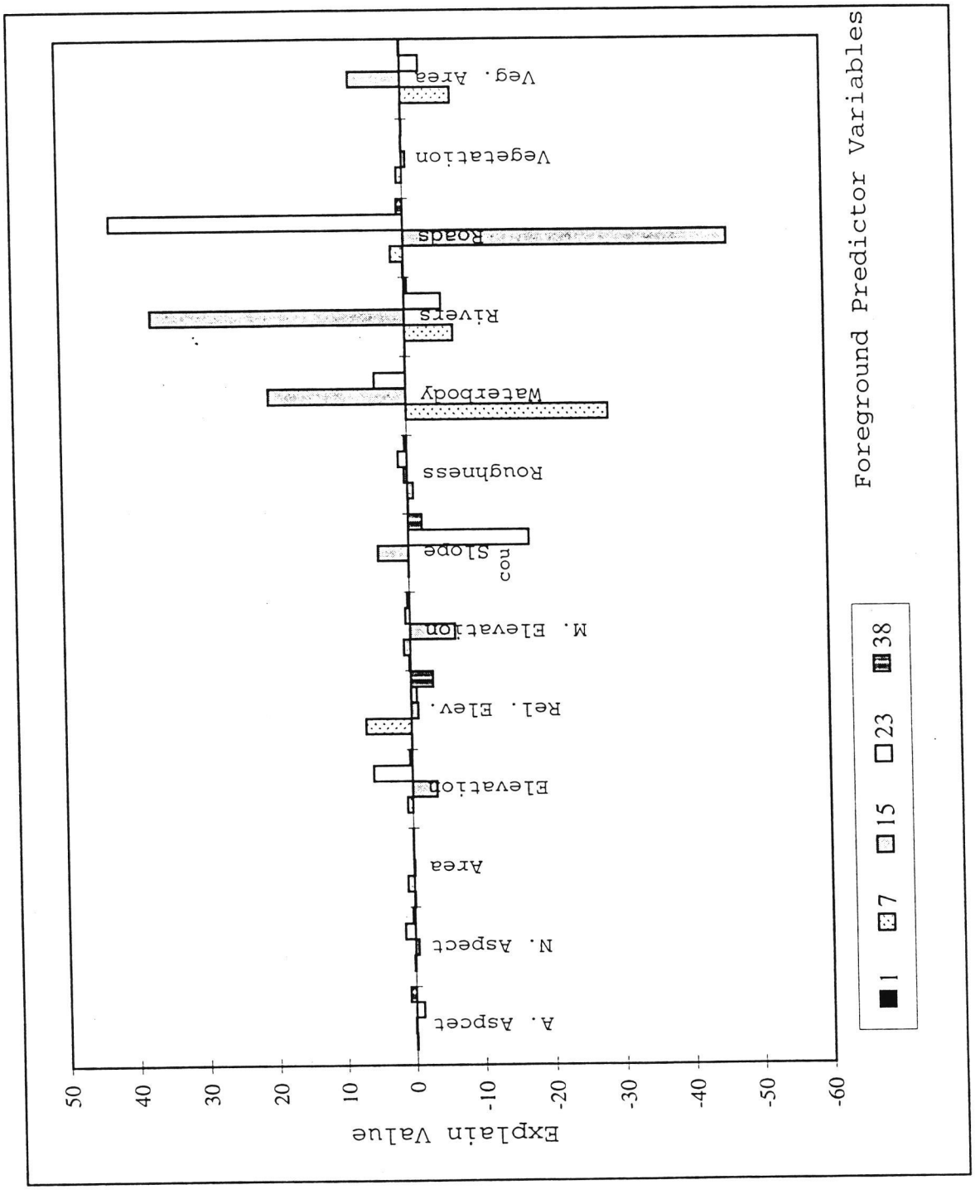


Figure 13 The Relative Importance of Background Predict Variables Contribute on the Scenic Beauty Value.

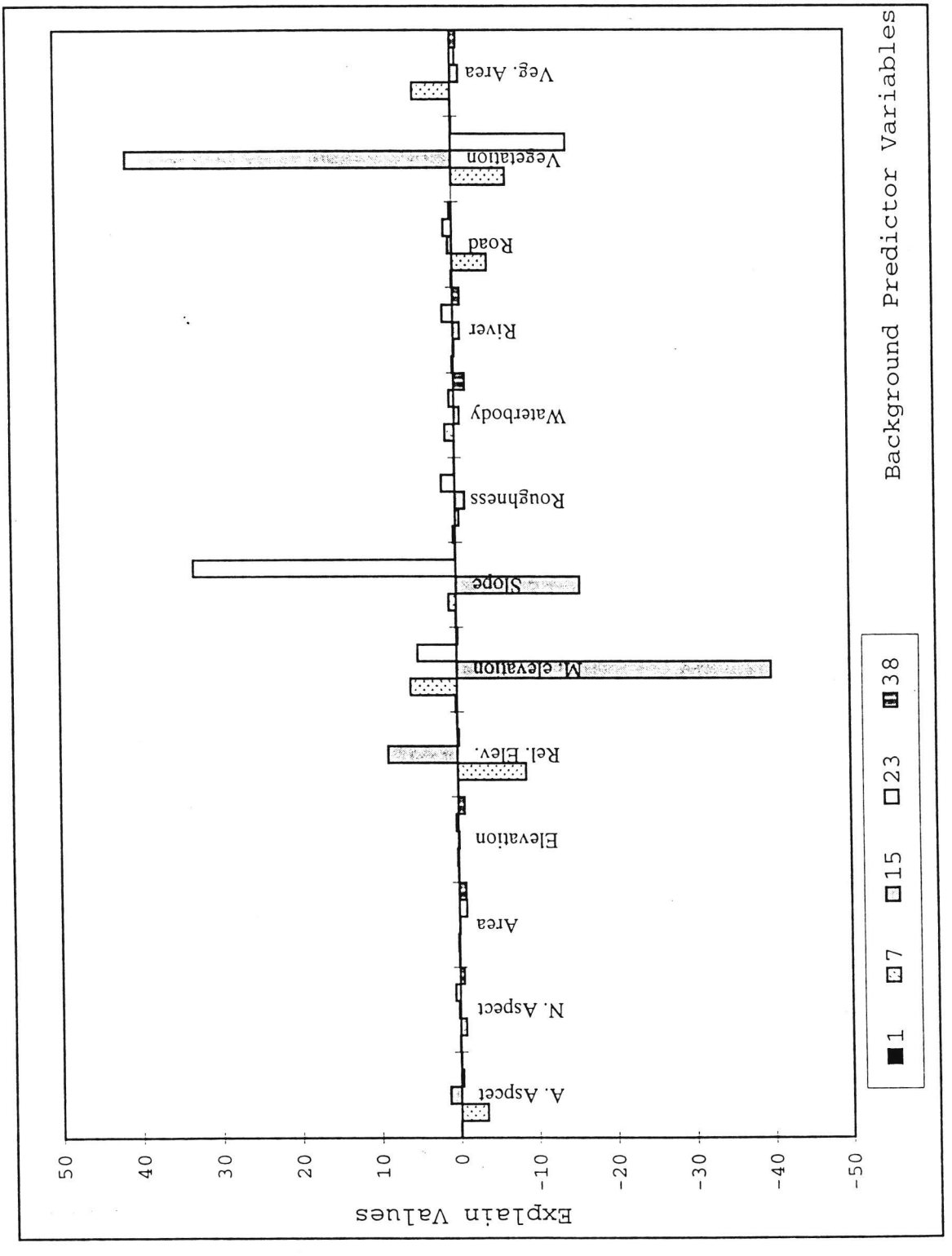
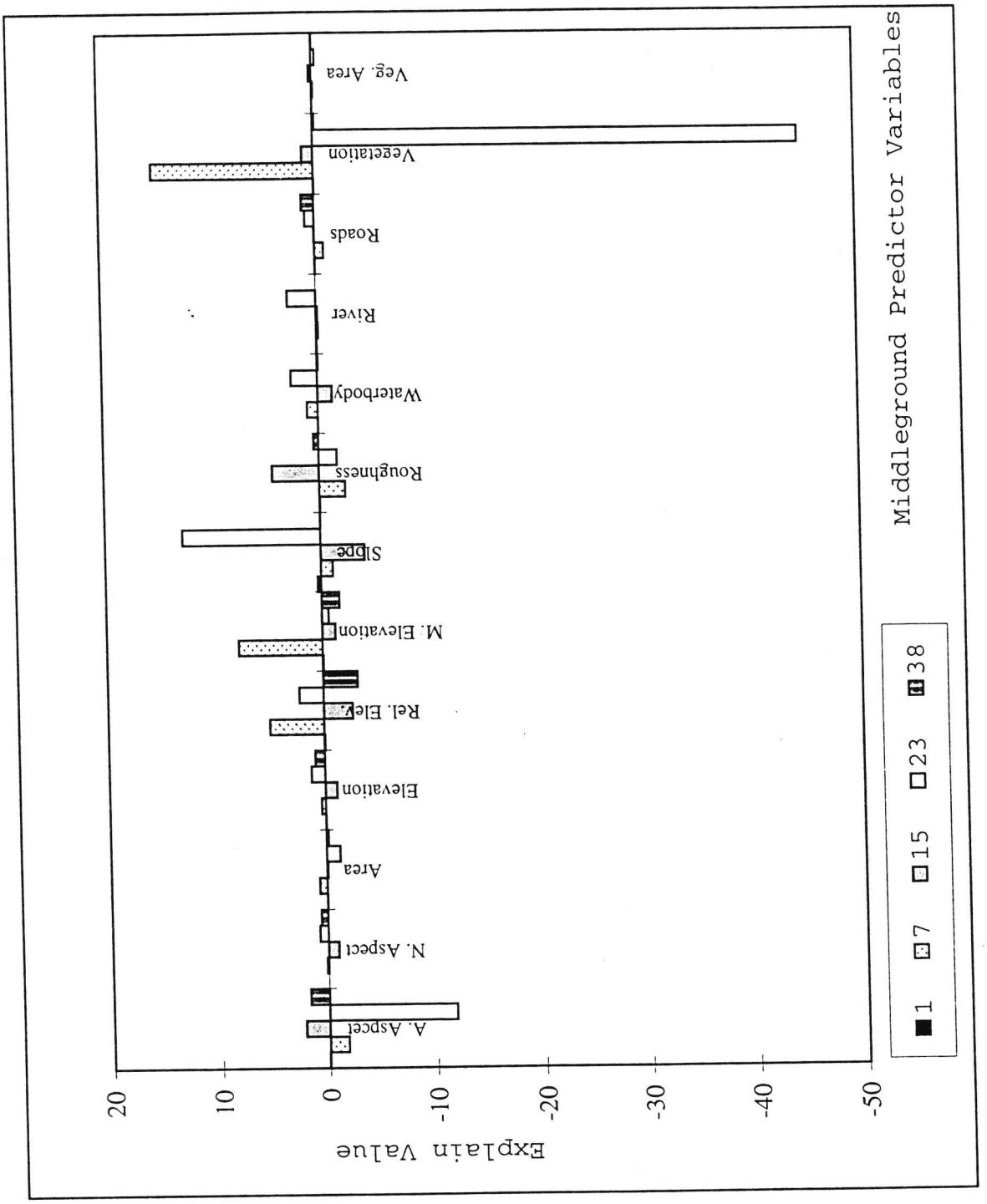


Figure 14 The Relative Importance of Middleground Predictor Variables Contribute on the Scenic Beauty Value



5 CONCLUSIONS

The goals in this study were to train a neural network to recognize patterns in scenic beauty ratings, which corresponded to known scenic beauty values for sample viewpoints and to associate those patterns with selected physical landscape variables. Undoubtedly, the neural network based vista SBE could predict vista scenic beauty.

Although this model provides an alternative approach for exploring the complex relationships that exist between natural environment and human perception. By using neural network to analyze scenic beauty not only requires knowledge of understanding neural networks, but quality and availability of geographic data are essential. For instance, predict results can be generated in a reasonable effort, only if geographic data is digitized and available.

Having used the neural network to analyze landscape preferences, interpreting the proportion of total variance explained by each predictor variable is a valuable procedure from a management perspective. The most important landscape features can be quickly identified, as well as the relative importance of other landscape features. In this way, not only are the potential areas for development can be identified, but potential directions for future research, management effort and concern are indicated.

Although these results pertain to a specific setting (forest areas) and cannot be assumed to apply in other environments, there still appear to reveal a promising future using the neural network as alternative to estimate vista scenic beauty in other types of settings.

The techniques described here, together, permit a quantitative scenic beauty estimation. It is based on manageable physical features that can reflect the scenically relevant landscape features of forest settings. Future research should examine more manageable features such as density of tree, and grazing area, etc. that weren't used in this study. Their correlation with scenic beauty and with other variables should be examined as well. Furthermore, it should be noted out that physical feature is just one of several factors that has influence on perceiving scenic beauty, and indeed that scenic beauty is heavily related to genetic variables, cultural background and personal experience. Those issues should be considered and incorporate into the neural-based vista scenic beauty model in the future research.

APPENDIX A: INTERVIEW INSTRUCTION AND QUESTIONNAIR

Our research depends upon the cooperation of students like yourself. **We are very grateful for your help in this study.**

Before beginning this experiment I am required to inform you that if at any time you do not feel completely comfortable participating in this experiment you should feel free to get up and leave -- no explanations will be necessary. The curtain over the door will be drawn only for ambient purposes and it in no way forces you to remain here at any time.

BACKGROUND

This study is part of a program of research to learn about people's perceptions of different environments. In this particular study we are interested in your perceptions of forested areas such as you might see on a visit to a National Forest. Forests are important for many reasons: For example, forests provide timber for construction, habitat for wildlife, and opportunities for outdoor recreation and for experiencing natural scenic beauty.

The purpose of this study is to investigate people's perceptions of the **natural scenic beauty** of different sites in the western US. You will view several different forest vistas and rate them on a 10 -point scale, where **0** indicates **very low scenic beauty** and **9** indicates **very high scenic beauty**.

THANK YOU

INSTRUCTIONS

A number of different forest sites will each be represented by a 360-degree panorama presented on the computer screen. Each panorama represents the full view available from a particular viewpoint in a much larger forest area. The procedures for presenting these vistas are still experimental, so the images are not all of the same quality. Please try to ignore the variations in color, brightness and any problems with "edge matching" in the 360-degree panoramas. Use the computer panorama to get an idea of what the vista would be like if you were there.

Please rate the forest vista -- not the computer image.

You will be able to look at any part to the panorama as long as you wish by using **the right and left arrow keys** on the keyboard to move your view to different parts of the panorama. The North segment of each panorama will always be presented first. A small "compass" will appear in the lower right corner of the screen to indicate which segment of the panorama is being presented.

When you have looked at each part of the panorama as much as you wish and you have decided how you want to rate the vista represented, press the **Esc**ape key. A screen will appear asking you to enter you rating (**0-9**) by pressing the appropriate number key. After you record your rating you can proceed to the next panorama by pressing the **space bar**. The first (North) scene of the next sample point will then be presented. You should look at each segment of the new panorama by using the arrow keys, and then enter Escape, record your rating for that vista, and press the space bar to go to the next panorama.

Continue this procedure until you have rated all of the panoramas (no more scenes will appear).

PREVIEW

Before you begin rating the vistas, you will look at a brief "preview" of the types of views you will be asked to rate. Samples of typical forest vistas will be shown briefly.

Each vista will be represented by a set of four individual scenes, roughly 90-degrees apart, showing what the forest would look like from that viewpoint.

As you look at the previews, try to imagine how you would rate the vista represented using the 0 - 9 scenic beauty rating scale.

Now that you have seen the preview, you can begin looking at the 360-degree panoramas and recording your ratings. Remember that you will view and rate the natural scenic beauty of different vistas in a large forest area. Each vista is represented by a 360-degree panorama. You will be able look at each segment of the view as much as you wish by using the arrow keys. When you have decided how you want to rate the vista, press the Escape key, and you will be prompted for your rating (0-9, using the number keys). Press the space bar to move to the next vista.

LANDSCAPE FEATURES

Now that you have finished rating the forest vistas, please take a few more minutes to help us better understand what makes some vistas more or less attractive than others. Recall the panoramas you just rated, and list the **positive** and the **negative landscape features** that affected your scenic beauty ratings. (A list of typical forest landscape features is attached for your assistance)

POSITIVE FEATURES	**NEGATIVE FEATURES**
_____	_____
_____	_____
_____	_____
_____	_____
_____	_____
_____	_____
_____	_____
_____	_____
_____	_____

Please look over your list of features and indicate which was the first (1), second (2) and third (3) most important **positive** feature by writing a **1**, **2**, or **3** next to that feature. Please repeat the process for the **negative** features listed.

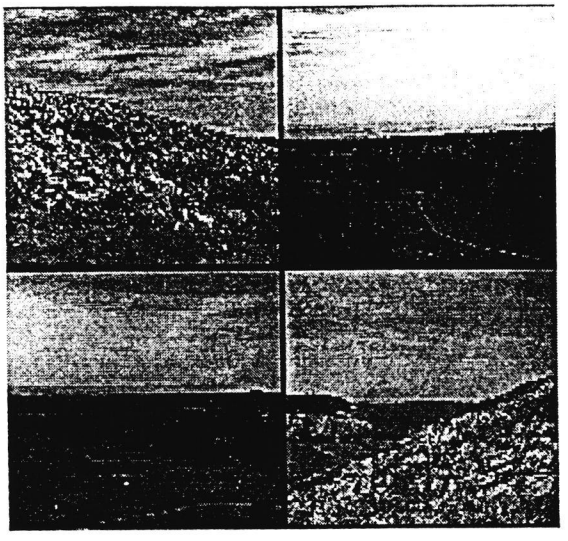
Finally, please write any other comments about the vistas or the panorama presentation, or rating procedure that you think will help us better understand your ratings. (Use the back of this page if needed)

LANDSCAPE FEATURE LIST

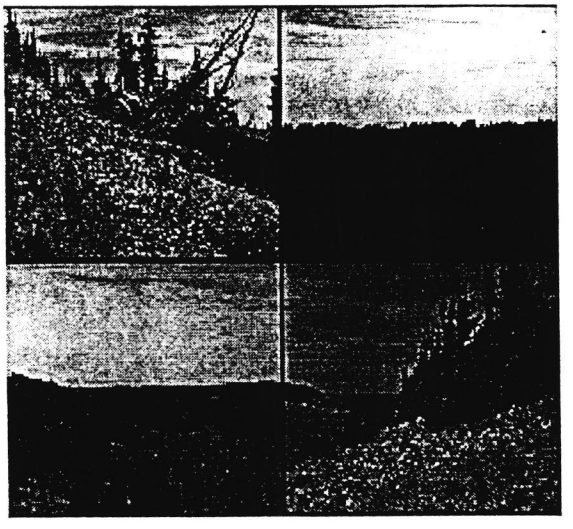
1. Brush covered hills
2. Gravel roads
3. Flowers
4. Confined (closed in) views
5. Open grassy areas
6. Diversity of topography (hills, valleys, ridges, etc)
7. Smooth elevation changes
8. Dead trees
9. Stands of aspen (white bark)
10. Campers or motor homes
11. Abrupt elevation changes
12. Grassy areas along streams
13. Tall dense stands of conifers
14. Mixed stands of conifers and aspen (white bark)
15. Rock outcrops
16. Lakes
17. Streams
18. Dirt roads
19. Buildings
20. Rocky, barren areas
21. Grassy meadows in front of tall dense trees
22. Rolling hills
23. Red rock cliffs and canyons
24. Fences, signs, etc
25. High viewing location
26. A diversity of vegetation patterns
27. Steep slopes
28. Changes in the depth of view
29. Wide open views
30. Cars
31. Power lines
32. Diversity of landscape colors
33. Paved roads

APPENDIX B: EXAMPLES OF THE PREVIEW IMAGES

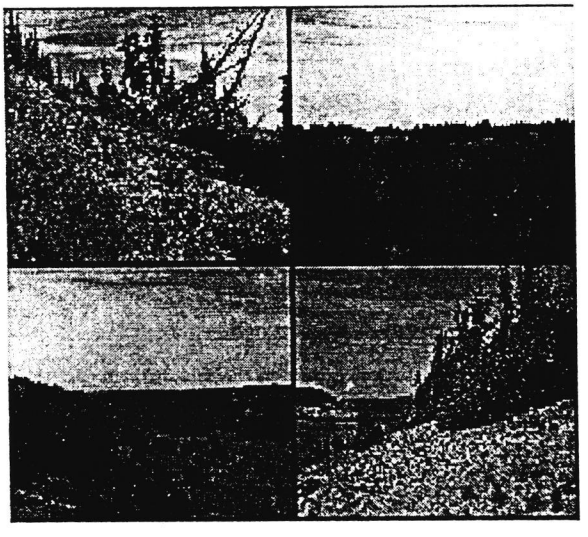
Preview Images of Viewpoint 9 Preview Images of Viewpoint 10

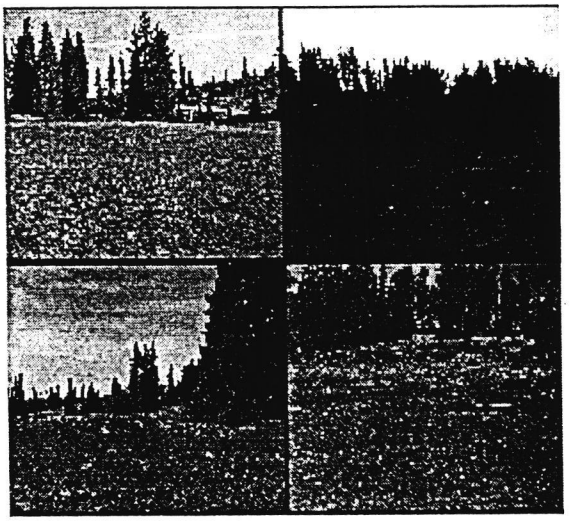


Preview Images of Viewpoint 11



Preview Images of Viewpoint 12





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<BODY ...>Michael J. Meitner
Terry C. Daniel

Vista Scenic Beauty Estimation Modeling: A GIS Approach

Abstract:

"Natural scenic beauty" is a concept that National Forest Managers must grapple with continuously when it comes to planning and decision making for the future of our forests. This resource has been difficult to define and has been the subject of over twenty years of research and development effort. Even more complex, are the vista perspectives, where in the viewer is typically elevated above the forest canopy and the view extends over relatively large expanses of forest landscape. This special case requires sophisticated techniques that take into account the levels of precision, reliability, and validity necessary to support public land management decisions. This paper discusses the components required for a GIS-based, "3-dimensional" prediction model for vista scenic beauty, including, 1) determination of significant viewpoints, 2) procedures for viewshed area specification and analysis, 3) defining the locus of vista scenic beauty (landscape or viewpoint), 4) the definition and computational methodology of relevant georelational landscape features, and 5) the statistical model used to generate predicted values.

Introduction:

This paper details one component, the *vista scenic beauty estimation modeling*, of the Scenic Beauty Management System, a conceptual model for a system to support planning and management of scenic beauty on National Forest lands. The primary role of the scenic beauty model is to translate forest conditions, existing and projected, into precise and reliable quantitative indices of scenic beauty. In addition, the system would provide guidelines for and assessments of alternative management designs for achieving specified forest scenic beauty objectives. Quantitative models and calibrated visual representations will be provided for communicating projected forest conditions within the multi-resource, interdisciplinary planning context, and with concerned publics/stakeholders, (Daniel, 1996) .

The term scenic beauty is intended to capture the central aspects of what has been labeled as *visual quality*, *scenic quality*, or *visual aesthetic value* (*-resource*, *-quality*). By whatever name, scenic beauty has long and consistently been recognized as an important resource of the National Forests. NEPA and NFMA both require the USDA Forest Service to incorporate "natural scenic beauty" in the management of public lands. Moreover, any broad survey of the American public will invariably identify scenic beauty as among the most important desires and concerns regarding the National Forests. Thus, a system for managing scenic beauty--i.e., for identifying, assessing, evaluating, projecting, manipulating and monitoring scenic beauty--must be a key component of any responsible forest planning and management system.

While scenic beauty in general is of interest, this paper will focus on outlining the procedure for the quantification of scenic beauty from a vista perspective. Vista perspectives are characterized by scenic overlooks, locations that offer relatively extensive views, as across a valley or over a river, lake or meadow. The viewer is typically outside the canopy of the forest and the depth of view may be measured in hundreds of meters. Breadth of views may extend up to 360-degrees, with both landforms and vegetation cover (especially when near the viewer) potentially restricting the view. Some parts of the viewshed (visible area) of a vista may be substantially below the height of the viewer and other parts may be well above the viewer. All of these characteristics of the vista are issues that must be dealt with if a predictive model is to be successful.

Modeling vista scenic beauty has typically focused on individual scenes, such as the view captured by a camera with somewhere between a 35 and a 55 mm lens (Buhyoff, et al, 1982; Shafer, 1964; Shafer & Richards, 1974; Vining, et al ,1984). These types of models are typically referred to as *picture plane* models. Originally, the unit of analysis for this project was going to be the vista as a point location, but because of the inability to validate this approach due to funding limitations we will define the vista as limited by view angle similar to a picture. Therefore, at any one vista point there will invariably be multiple vista viewsheds for which the model will attempt to predict a value. Variables found important in the picture plane models include presence and height of mountains, percentage of the scene that is covered by forest canopy, presence and size of water features (lakes or streams) and other relatively large scale land cover variables. These factors are commonly determined by placing a grid over the picture and manually counting the number of cells that contain the attribute of interest. The effects of all of these land cover variables differ depending upon the distance from the viewer (foreground, midground, background) and probably upon the visual aspect (angle of intercept of the line of sight with the main axis of the feature). Vista scenic beauty, then, has been found to depend upon the particular features present in the view, the pattern and inter-relationships among those features and whether these features and patterns occur close to or distant from the viewer (i.e., in the for-, mid- or back-ground of the scene).

Thus, vista scenic beauty is tied to the features of the landscape and to the particular location (the viewpoint) from which that landscape is viewed. It is impossible to refer to the "inherent" vista scenic beauty of any given landscape feature without specific reference to the viewpoint(s) from which it is viewed. Features that make an important positive contribution to scenic beauty from one view point may not be visible at all from another viewpoint, or may even have a negative effect on other views. Thus, the "scenic beauty" of a given landscape feature is conditional upon the viewpoint(s) from which that feature can be viewed. In some contexts it may be meaningful to refer to the scenic beauty of a feature, based on its contributions to the multiple viewpoints from which that feature can or might be seen, but for the purposes of this project the I will not attempt to present how that would be done. Suffice to say that once the viewsheds are quantified in terms of scenic beauty, it would be relatively easy to reverse one's thinking and predict values for objects.

These concerns offer an additional layer of complexity that differs from the typical near-view perspective of scenic beauty from which vista modeling draws much of it initial framework, but the underlying concepts and some of the procedures are the same. The most successful approaches to assessing and projecting near-view scenic beauty have been based on the public perception or "psychophysical" model. This technology has been well tested and its reliability, validity and utility confirmed in numerous studies (Brown & Daniel, 1986; Buhyoff, et al , 1986; Daniel, et al, 1977; Daniel & Schroeder, 1980; Zube, et al, 1975). Scenic Beauty Estimates are obtained by presenting representative samples of individuals with color slides of the forest in question and asking them to rate those slides according to their "natural scenic beauty" on a ten point scale. These raw scores are then transformed by statistical procedures, outside the scope of this paper, into Scenic Beauty Estimates. Those estimates will then be related through multivariate statistical techniques to inventoried or estimated forest features (numbers, sizes and species of trees, volumes of downed wood, shrubs, grasses, etc.) to create quantitative scenic beauty prediction models. By design, these quantitative models will take as input the biological and physical forest features. Thus, as future conditions of the forest are projected by the biological models, estimates were provided of the associated changes to be expected in perceived scenic beauty indices (Brown & Daniel, 1984; Daniel & Boster, 1976).

The goal of this paper is to specify the explicit structure of a model that is capable of predicting scenic beauty values based on data associated with a view from a particular vista location. Specifically, to develop and test statistically-based *vista scenic beauty estimation* assessment methods and prediction models for restricted (mid-range) and panoramic views characteristic of forest landscapes in visually sensitive areas of the Dixie National Forest. While much research has been undertaken over the last 15 years in the development, validation and subsequent refinement of the SBE models for the near-view perspective, very little effort has been expended on vista perspectives, and no adequate models exist.

Opportunities for vista scenic beauty modeling efforts are greatly enhanced by modern Geographic Information Systems technology. In particular, GIS overlay and spatial modeling techniques can be combined with viewshed analysis functions to develop bio-physically based models. As discussed previously, vista scenic beauty estimations must be modeled on a viewpoint basis. Thus, the area that is visible from a viewpoint must be made explicit and a viewshed must be specified. Furthermore, changes in the bio-physical landscape features, such as; topography, vegetation cover, streams and lakes that fall within the viewshed of a designated viewpoint, along with contrasts, shapes and patterns of these features, within the visible area (viewshed) for a given viewpoint would serve as the independent variables in quantitative models of vista scenic beauty. Relevant landscape features will have to be geo-spatially referenced both in terms of their distance and azimuth relative to the viewer (viewpoint), as well as their extents, distributions and interrelationships within the viewshed. Because detailed three-dimensional, geographically distributed landscape features are the logical input parameters for such a model, a GIS platform is necessary for the adequate spatial analysis of such complex variables.

A great deal of thought must be put into the creation of such a vista model. Independent variables must be chosen from the multitude of possibilities to serve as predictive parameters in our statistical model and as with any statistical model one runs the risk of including too many variables and ending up with a model that merely capitalizes on chance. Therefore we must seek to discover a more parsimonious subset of the larger set of possible variables that we hypothesis to explain our dependent variable of interest, *vista scenic beauty estimations*. This paper serves the purpose of delimiting a concrete target model through which the process of hypothesis testing can begin and eventually by the process of model refinement, the solidification of a final product for decision management will emerge.

Methodology:

A stratified sample of 24 viewpoints were selected from the possible set of 70 total viewpoints in the Dixie National Forest based primarily on the availability of data for surrounding forest stands. A stand is loosely defined by the Forest Service as a predominantly homogeneous, polygonal area of vegetation. At each viewpoint a series of sixteen photographs were taken, (image 1) in order to accurately represent a 360-degree panorama view of the location. The photographs from the sampled vista viewpoints were shown to representative volunteers, ratings were collected and scenic beauty indices were computed for each view from a vista. Reliability measures indicate a high level of agreement among observers and the viewsheds selected represent a significant proportion of the range of scenic beauty values.

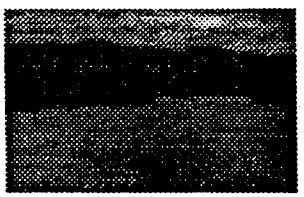

Image 1: A typical mid-range vista

For the sake of simplicity in this preliminary analysis only one of the 16 views from each of the 24 vista points were included. The orientation of these views were systematically selected so that the resulting viewshed was one that contained reliable stand-level data. Each view was defined by its point location, (X, Y, and 1.68 meter offset from the extrapolated surface location) and orientation information, defined by two angles of azimuth and two vertical angles. Since a 50mm lenses was used to take the photographs the view was defined as 40 degrees of visual angle horizontally by 27 degrees vertically, therefore a picture taken pointing due north would be defined in the visibility command by the following parameters: offsetA = 1.68, azimuthA = 340, azimuthB = 20, vert1 = 14, and vert2= -13. The parameters offsetB, radius1, and radius2 were left set to their defaults. Visibility coverages were then calculated for all the views using 30

meter USGS DEM data concatenated with the stand height data derived by the forest service to produce a DEM representing the canopy of the forest, as the *in lattice*. "Projectcompare" was set to full so that the curvature of the earth and atmospheric distortions were taken into account in the calculation. The output coverages were polygonal with the frequency of observation specified as the visible-code of the polygons. These were then unioned with the original polygonal stand coverage in order to determine the underlying distribution of stands that made up the viewshed. A frequency table was then created so that the area represented by each of the stands in the viewshed could be totaled and converted to percentages of the total area of the viewshed.

The percentage of area was the variable used to relate the viewsheds back to the bio-physical stand data collected by the Forest Service. Each viewshed was then described by the weighted average of stand information visible to the observer from the point and orientation specified. In other words, viewshed 1, which is comprised of 30% stand A and 70% stand B, would be represented by .3 * (# of aspen, # of spruce/fir, etc.) + .7 * (stand B's data). These weighted sums would then be used to calculate average percentages of tree type represented. This allowed us to begin to build multiple regression models to predict the scenic beauty estimates of the commensurate viewsheds.

Conclusions:

The preliminary model, SBE = 6.025892 + 1.06729e-05 (Total Area Seen) + -.014715 (%Spruce/Fir) + .010804 (%Aspen) - .007154 (%Dead Trees) - .012179 (%Meadow) + .070320 (# of Stands in the view), yields a R squared of .34, which unfortunately is not significant. As the modeling effort continues we expect to see this increase and move beyond significance, but there are many problems that still need to be overcome. The greatest of which is the fact that the calculation of viewshed areas is somewhat dependant upon chance. The 30 meter resolution of the input lattice causes the creation of sliver polygons when this layer is unioned with the polygonal stands layer. This leads to a situation where the areas of stands in a particular viewshed are arbitrarily specified based on the view point's location along with the stand boundaries, in reference to the cells of the grid used. One possible solution to this problem that we are presently pursuing is the idea of the percentage of the stand seen as being represented by the length of the arc of the leading edge of the stand bounded by the viewshed. This would eliminate a great deal of measurement error in the calculation of the percentages of represented stands, which in turn degrades the data driving the modeling procedure, causing the relationships to be muddied.

Ultimately, we would like to take into consideration the relative densities of the stands, but because approximately half of our stands currently depend on coarse GAP data it is impossible to compute average viewshed tree densities. As more cases are introduced it will be possible to minimize the number of viewsheds dependant on the GAP data, therefore increasing the resolution of the underlying data. This information is also crucial to the approximation of textural information contained in the view which may also be of importance. The incorporation of a distance weighting scheme in order to account for inevitable visual differences of near and far objects is also a variable we would ulitimately like to include. As this ongoing process continues to evolve a more significant and robust model will emerge to fullfull the needs of Forest and other land managers so that they may better administer the duties with which they are charged.

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A METHOD FOR ASSESSING NEAR VIEW SCENIC BEAUTY MODELS: A COMPARISON OF NEURAL NETWORKS AND MULTIPLE LINEAR REGRESSION

by

Myles Martin Flynn

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DEDICATION

I would like to dedicate this thesis to my mother, Mrs. Elizabeth Fahey and my father Mr. Myles Leo Flynn, for their emotional and financial support throughout my academic career.

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Abstract

With recent advances in artificial intelligence, new methods are being developed that provide faster, and more consistent predictions for data in complex environments. In the field of landscape assessment, where an array of physical variables effect environmental perception, natural resource managers need tools to assist them in isolating the significant predictors critical for the protection and management of these resources. Recent studies that have utilized neural networks to assist in developing predictive models of scenic beauty that have typically utilized linear regression techniques have found limited success. The goal of this research is to compare NN's with linear regression models to determine their efficiency predictive capability for assessing near view scenic beauty in the Cedar City District of the Dixie National forest (DNF). Results of this study strongly conclude that neural networks are consistently better predictors of near view scenic beauty in spruce/fir dominated forests than hierarchical linear regression models.

Introduction

Public sentiment and legislative mandate require that not only commodity based resources, but also esthetic preferences be considered when planning and implementing natural resource management decisions in this nations public lands. National concern for the preservation of landscape aesthetics is reflected in numerous legislation including: the Multiple-Use Sustained-Yield Act of 1960, the National Environmental Policy Act of 1969, the Forest and Rangeland Renewable Resources Policy Act of 1974 and the National Forest Management Act of 1976. Much of this legislation directly addresses amenity resource issues such as the preservation and management of aesthetic, wildlife, recreation and wilderness resources.

Landscape scenic beauty is arguably one of the most important natural resources of our public lands. Increases in disposable income and free time along with urban population growth has led to a dramatic upsurge in recreational use of national public lands. The once strictly commodity based management practices of the past are coming under increased public scrutiny. This public concern has led to a flurry of research in the area of aesthetic preferences. A 1976 United States Forest Service Research Paper, (Daniel and Boster, 1976) highlighted three reasons for quantifying relative aesthetic preferences for landscapes, resulting from forest management practices, including:

"1. Better integration with other resources and products.

Increasing complexity in planning and management of public lands leads to problems integrating traditional economic concerns i.e. timber, forage, water, with less tangible products, i.e. esthetics, wildlife, and recreation.

2. Better justification for land use decisions.

Resources that can be objectively measured should be, so that decisions can be based on as much substantive evidence as possible. Because the public is seeking more information about and more involvement in public land planning, decision makers are under increased pressure to better justify management decisions. Objective measurements of scenic beauty would provide better justification to an increasingly concerned and skeptical public than do intuitive assumptions or unsupported expert opinions.

3. Restoration of the client -architect relationship.

Accurate determination of esthetic perceptions and preferences is essential if the client-architect relationship is to be a reality in the context of public land management."

Of the many resources we use, preserve, and try to improve, scenic beauty has proven one of the most difficult to measure in an objective, scientific manner. No doubt this is because beauty is only partially defined by characteristics of the environment, and depends, in large part, upon the human subject (Daniel and Boster 1976).

Extensive research has been conducted regarding the quantification of qualitative human response data (i.e. aesthetic preferences). One application designed to quantify such a construct is the Scenic Beauty Estimation (SBE) approach, developed by Daniel and associates (Daniel and Boster 1976; Brown and Daniel 1984, 1990). This method utilizes a combination of visual stimulus response ratings and RMRATE, a statistical computer program, to determine scenic beauty estimates for a variety of landscape settings. This process relies heavily upon field data collection in the form of either photographs or, alternatively, in real world ratings by human subjects. One drawback of this approach, is the time intensive nature of the data collection process.

A possible alternative to collecting human visual response data is to utilize biophysical forest stand composition data, which is routinely collected by the United States Department of Agriculture Forest Service (USDAFS). Brown and Daniel (1984) experimented with using linear regression models to predict scenic beauty estimations based on this biophysical stand data with encouraging results (Brown and Daniel, 1984). There has also been research conducted using neural networks and biophysical data to predict scenic beauty (Bishop, 1996). Aside from Bishop (1996), little research has been conducted that compares these two approaches in terms of which process is more or less reliable.

1.0 Problem Statement

Public perceptions of the scenic beauty are carrying increasing weight with regard to resource management decisions in the National Forests of the United States. Historically, the established methods for managing resources or developing facilities are frequently met with vocal objections if not legal obstructions, because managers fail to consider the impact of their actions on scenic beauty and fail to involve the public in the decision making process (Magill, 1990). Those who perform analysis in support of the natural resource decision making process are required to interpret a wide variety of data in both spatial and nonspatial formats (Deadman et al. 1996). These resource mangers have the opportunity to take advantage of emerging technologies in computer modeling and simulation to evaluate the relationships between these spatial and nonspatial data to assess the impact of management decisions prior to implementation. One such technological approach is the utilization of Neural Networks (NN) to simulate human response.

The capability of neural networks to include both qualitative and quantitative data makes them a valuable decision support tool for natural resource management. A 1995 study in Hoosier National Forest concluded that a NN coupled with a GIS provided an effective method for combining qualitative and quantitative variables to provide decision support for natural resource managers (Gimblett et al. 1994; Gimblett and Ball, 1995) As more qualitative and qualitative data becomes available, many previously untested relationships are emerging. Empirical testing of these relationships may result in valuable

knowledge previously unavailable to natural resource land managers resulting in better informed management decisions.

In the area of scenic beauty estimation, much of this empirical testing has relied on the use of linear regression models to tease out the significant landscape variables that contribute to perceived scenic beauty. According to Bishop (1996), there are two obvious problems however that exist with the linear multiple regression models. The first is that it is unlikely that human perceptions would follow a linear model. The second is that there are inevitable interdependencies between the factors which cannot be properly included in a linear regression model.

To address these problems, current research is testing the effectiveness of utilizing neural networks for scenic beauty estimation (Bishop, 1996). Neural networks have also been utilized in a landscape planning context (Gimblett et al. 1994). Openshaw (1993), also concluded, after comparing neural networks and conventional modeling techniques, that there were possible advantages to the neural network approach including; better performing models, greater representational flexibility, handling of explicitly noisy data and the potential of neural networks in other fields. Bishop (1996), concurred and identifies the potential, based on their ability to deal with non-linear and factor independence, that neural networks may provide for more stable results that traditional regression models.

Little research however has been conducted that compares the linear regression model to a neural network approach and some questions exist as to which, if either, approach is more reliable . In Bishop (1996), a number of research questions were

presented about the relationships between neural networks and linear regression models. What is the predictive capability of the neural network compared with a regression model based on the same variables? How do the residuals in the regression compare with the misfits in the neural net model?

2.0 Background Literature

2.10 Scenic Beauty Estimation Model and Multiple Linear Regression

The Scenic Beauty Estimation Model (SBE), first introduced by Daniel and Boster (1976), estimates scenic beauty based on human perceptual responses. The SBE method measures public "perceptual preference" for various landscapes through a carefully defined system of rating color slides. During its evolution the SBE method has, through extensive testing and application proven to be a reliable and valid measure of perceived scenic beauty in a varying range of forest management settings. Furthermore, Daniel et al. (1976), proves that differences in SBEs indicate true differences in the perceived scenic beauty of the landscapes, independent of differences in observers standards.

A typical application of the SBE method includes representation of forest landscapes in the form of systematically sampled 35mm color slides. These slides are then rated by a number of respondents using a 10-point scale and the responses are subjected to a psychometric scaling routine using a computer program, RMRATE (Daniel et al. 1990). This program provides a standardized (interval scale) quantitative index of preference or a perceived scenic beauty estimate (SBE). The resulting SBE (perceptual) scale value can then be related to forest biophysical data (e.g. basal area, species composition, diameter classes). Traditional methods rely on linear regression models to determine which biophysical (independent) variables best explain the variance in the SBEs (dependent variable).

According to Daniel, natural scenic beauty is assumed to result from the effect of landscape biophysical features of the perceptual and judgmental processes of the human observer (Daniel et al. 1973; Daniel and Boster, 1976; Brown and Daniel, 1987) From this, Daniel concludes that perceived scenic beauty can be related, via quantitative models, to measures of the biophysical features of the landscape. Biophysical forest stand data is routinely collected by the USDAFS for use in timber sales and other management activities. The field data is then entered into RMSTAND, a statistical computer package which outputs descriptive statistics for each surveyed stand. The SBE model takes advantage of this relationship and applies multiple linear regression statistics to isolate the critical biophysical features contributing to perceived scenic beauty, and to predict scenic beauty based on landscape features.

The basic SBE model has been widely used and researched, (Arthur, 1977; Buhyoff and Wellman, 1980; Schroeder and Daniel, 1981; Buhyoff, Wellman et al. 1982; Hull and Buhyoff, 1983; Schroeder and Brown, 1983; Brown and Daniel, 1984; Brown and Daniel, 1986; Brown and Daniel, 1987; Ribe, 1989; Ribe, 1990) but the most successful of results focus on near view landscape scenes. Daniel describes near view scenes as, "representing the forest as it would typically appear for a viewer who is within the forest and whose view is generally constrained to no more than a few hundred yards."

2.20 Near View Scenic Beauty Estimation Model

Near View Scenic Beauty Estimation Models (NVSBE), predict perceived near view scenic beauty of forest landscapes from within the forest canopy. According to Daniel (1976), the near view application of the SBE model has been extremely successful in relating the biophysical forest stand features, via multiple regression models, to the perceived scenic beauty of a variety of interest groups. The near view model again relies on relating the perceived scenic beauty of forest scenes, via color 35mm slides, to the biophysical forest stand data collected by the USDAFS. The near view model also assumes that the field of vision for any scene is completely contained within a particular forest stand.

Using this technique, Daniel (1976), has been able to predict the perceived near view scenic beauty of stands for which accurate biophysical stand data exists. These SBE models and methods have been proven over time to be reliable and valid procedures for determining scenic beauty estimations for a variety of southwestern and other forest conditions. Daniel (1976), has also developed a method for determining vista scenic beauty (i.e. beauty of larger viewsheds) across multiple stands, based on similar methods. The vista models methods, however are beyond the scope of this research and will not be addressed.

According to Bishop (1996), there are two obvious problems that exist with the linear multiple regression models. The first is that it is unlikely that human perceptions would follow a linear model. The second is that there are inevitable interdependencies between the factors which cannot be properly included in a linear regression model.

2.30 Neural Networks and Natural Resources

Advances in computer technology in the 1980's and 90's has contributed to an increase in its affordability and availability. One result of this computer revolution is that Neural Networks (NN) and other modeling, simulation and prediction techniques are now becoming included in the tool palette of public land management agencies. Neural Networks are massively parallel, interconnected networks, of simple (usually adaptive) elements and their hierarchical organization, which are intended to interact with the objects of the real world in the same way as biological nervous systems (Gimblett et al. 1995). NN's have recently been employed in a variety of resource based disciplines including landscape planning (Gimblett et al. 1994; Bishop, 1996; Deadman et al. 1996) and architectural design (Coyne and Yokozawa, 1992).

Neural networks are based on learning by example rather than relying on hardwired computer programming. NN's treat the space between stimuli (inputs) and responses (outputs) as a network of nodes whose individual responses are triggered by the inputs and the other nodes of the network (Rumelhart and McClelland, 1987) Muller and

Reinhardt (1990), define a neural network as a graph with the following mathematical properties:

1. a state variable n_i is associated with each node i.
2. a real-valued weight w_{ik} is associated with each link (ik) between two nodes i and k:
3. a real-valued bias B_i is associated with each node i:
4. a transfer function $f_i\{n_k,w_{ik},B_i,(k(not=)i)\}$ is defined, for each node i, which determines the state of the node as a function of its bias, of the weights of the incoming links, and of the state of the nodes connected to it by these links.

The above stated transfer function is commonly denoted as f (Sum $w_{ik}\ n_k - B_i$), where $f(x)$ is a discontinuous step function or a smoothly increasing generalization known as a sigmoid function (Bishop, 1996). When initialized, the neural network software assigns randomly calculated weights to the nodes between the input layer and the output layer. This intermediate layer is know as the hidden layer, of which there may be more than one. The network then adjusts the weights at each cycle of the training session to maximize the matching of known output values to NN output values (Bishop, 1996). Commonly this type of model is trained on a number of sets of input and output data. The model's predictive capability is then tested by supplying it with new input data (independent variables) and allowing the NN to determine the output values (dependent variable). If the NN is properly trained, the output values predicted by the NN will closely resemble the known output values. Both Openshaw (1993) and Bishop (1996) agree that not only do NNs have the potential to produce better performing models, with greater

representational flexibility, and possess handling of explicitly noisy data, they also, based on their ability of deal with non-linearity and factor independence, may provide for more stable results than traditional regression approaches.

2.40 Summary of Literature

The study of perceived scenic beauty has traditionally relied on the utilization of linear regression models to isolate the biophysical landscape elements that contribute the most to the prediction scenic beauty. Some research, however, argues that linear regression models may not adequately handle non-linear relationships and factor interdependence issues that may exist in human perception of scenic beauty. The recent development of neural network technology provides an alternative method for isolating the landscape variables critical for the prediction of scenic beauty. NN's unlike, linear regression models are better able to handle non-linear relationships and factor interdependence. Bishop (1996), highlights a need for research that compares the linear regression approach to the neural network approach to determine if either approach is a more successful tool for predicting scenic beauty.

The application of NN's for modeling, and simulation has been employed recently in a variety of disciplines. There has, however, been little research using NN's to predict landscape preferences. The research that has been conducted has specifically addresses perceived scenic beauty in vista or panoramas situations and seeks to derive scenic beauty in situations where the stimuli includes distant views (Bishop 1996). No research has

been conducted that utilizes NN's to predict perceived scenic beauty in near view scenes, where the stimuli includes areas which both are: contained completely within a particular forest stand, and where view thresholds do not exceed approximately fifty meters.

3.0 Goals and Objectives of the Research

The goal of this research is to compare neural networks with hierarchical linear regression models for predicting near view scenic beauty. Specifically, this research will compare and contrast the differences between the predictive capability of a neural network and a linear regression modeling approach for estimating scenic beauty based on the same dependent and independent variables.

The objectives of this research is are:

* To investigate, summarize, and test methodologies for the prediction of near view scenic beauty;
* To develop, modify, and assess a series of multiple linear regression models designed to predict near view scenic beauty, utilizing United States Department of Agriculture Forest Service (USDAFS) stand data and related scenic beauty estimation data;
* To develop a series of neural network models that mirror the structural components of tested multiple linear regression models.
* To compare the predictive capability of the linear regression model with that of the neural network based on the same dependent and independent variables;

4.0 Research Methods

4.10 Data Collection and Photographic Sampling

The section outlines the methods and methodology used for data collection and photographic sampling including: (Section 4.11), Collection and processing of RMStand data, (Section 4.12) collection and procession of near view photographs, (Section 4.13) running of the student subjects, and (Section 4.14) extraction and processing of biopyhsical variables from RMStand data.

4.11 RMStand Data

The forest stand biophysical data was acquired from the Cedar City District Office of USDAFS, in Cedar City Utah. The USDAFS uses large scale aerial photographs to delineate homogeneous forest stand "location". The forest stands which are then divided into smaller areas called forest stand "sites". For example there would be only one forest stand location 126, which may have any number of forest stand sites. This biophysical data is then used as input into RMStand, a statistical computer program developed by Dr. Terry Daniel. RMStand computes summary statistics of each forest location/site (see appendix A). The output from RMStand is then input into an Excel spreadsheet, to be used later as input (independent variables) into the NN and LRM.

4.12 Study Site and Photographic Sampling

The series of near view photographs were taken in the Cedar City District of the Dixie National Forest (DNF), Utah (Figure 1). The Cedar City District of the DNF is located in southwestern Utah, thirty miles east of he town of Cedar City and encompasses approximately five hundred sixty square kilometers (Figure 2). The DNF was chosen as a research site due to the long history of studies in this area related to the visual impacts of spruce bark beatle infestations. The stands were photographed in July of 1995 and 1996 by: Myles M. Flynn Research Specialist The University of Arizona Advanced Resource Technology Group, Edward Weidemann Masters Student The University of Arizona, Mike Meitner Phd Candidate The University of Arizona, and Michelle Hawks, GIS technician Missouri Department of Conservation. The photographic field work was conducted under the direction and supervision of Dr. Terry C. Daniel The University of Arizona, Department of Psychology and School of Renewable Natural Resources, in conjunction with a series of perception studies for the USDAFS Cedar City District.

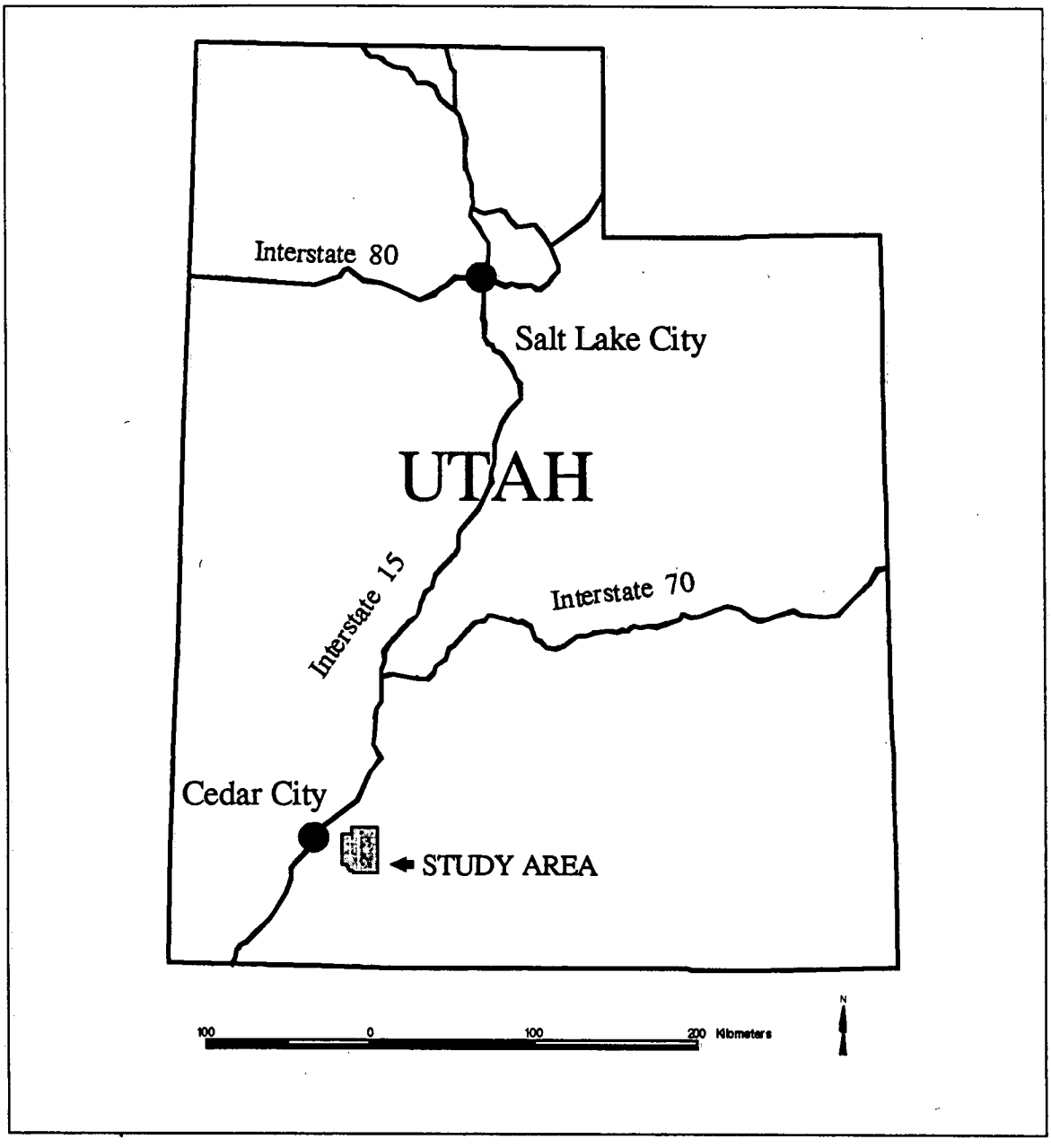

Figure 1. General Study Area Reference Map - Cedar City District, DNF, Utah

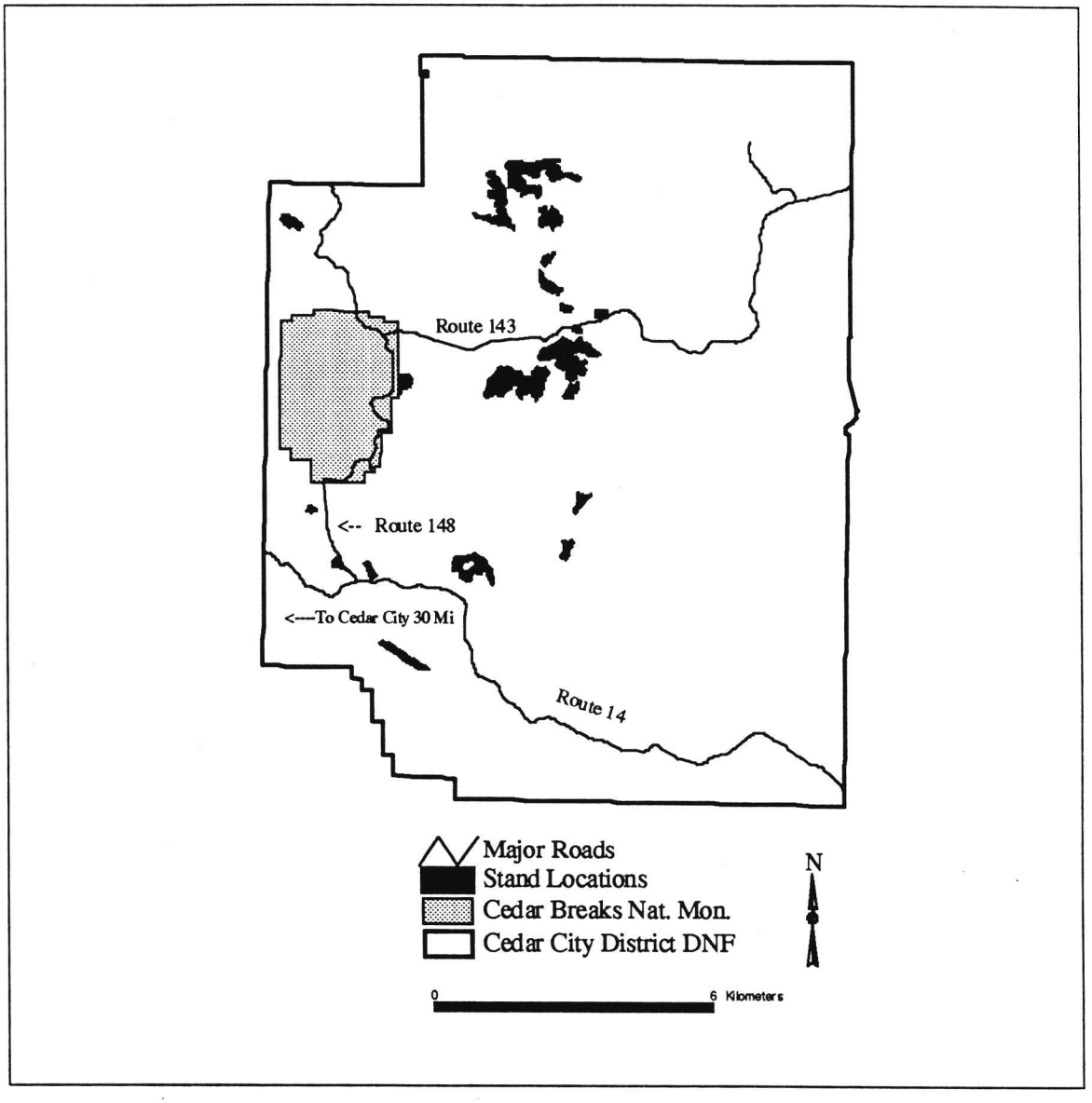

Figure 2. Study Site Location Map - Cedar City District, DNF, Utah

The photo points were chosen based on the availability of forest stand biophysical data which is compiled for each forest stand by the United States Department of Agriculture Forest Service (USDAFS). Large scale aerial photographs were utilized to locate targeted forest stands and to choose photo point location. Four photo points were

chosen within each target forest location/site. These points were chosen as to best represent the typical condition existing within each stand. A panorama is photographed from each point consisting of eight photographic slides 45 degrees apart for a total of 32 slides for each location/site.

4.13 Student Subjects

The photographic slides are randomized and rated for scenic beauty by human subjects. The human subjects are assembled from a pool of psychology students at The University of Arizona, Environmental Perception Lab. The photographic slides are randomized and rated for scenic beauty by each human subjects. Subjects are asked to rate each slide on scale of 1 to 10, one being the lowest scenic beauty value and 10 being the highest scenic beauty value. A baseline is used to normalize the ratings within groups and each slide is viewed by no less than 30 human subjects The raw scenic beauty values for each slide are then analyzed in RMRate (Daniel et al. 1990). RMRate then uses baselines to normalize the origin and range of observers ratings within groups of observers, producing Scenic Beauty estimates for each slide. The output from RMRate is input into a Microsoft Excel spreadsheet and the SBE ratings for the 32 slides associated with each location/sites are then averaged to produce a composite SBE's for that location/site.

4.14 Biophysical Variables and RMStand

Biophysical variables were extracted from the RMStand output, 27 in total, consisting of 15 explicit variables (extracted directly from RMStand) and 12 implicit variables (computed from RMStand variables). The explicit biophysical variables include: Average Diameter Breast Height Fir (AvDbh_fir), Average Diameter Breast Height Total Trees (AvDbh_Tot), Average Diameter Breast Height Aspen (AvDbh_As), Average Diameter Breast Height Spruce, (AvDbh_Sp), Dead Basal Area (Dead_Basel), Basal Area Aspen (Ba_Asp), Basal Area Fir (Ba_Fir), Basal Area Spruce (Ba_Sp), Number of Aspen (No_Asp), Live Basal Area (Live_Basal), Number of Spruce (No_Sp), Total Basel Area (Tot_Basal), Large Trees Greater Than 5 inches (Lg_Tr_Gt5), Number of Fir (No_fir), Number of Total Trees (No_Tot_Tr). These variables were then input into Microsoft Excel and divided by factors of ten to normalize their values to between 0 and positive 1.

The implicit biophysical variables include: Number of Fir and Number of Spruce (No_F/S), Average Basal Area for all Trees (Ave_Basal_Per_All_Trees), Percent Fir Trees (Per_Fir_Tr), Percent Spruce Trees (Per_Sp_Tr), Percent Fir Trees Plus Percent Spruce Trees (Per_Fir_Tr+Pers_Spr_Tr), Percent Aspen Trees (Per_Asp_Tr), Percent Basal Area Fir (Pers_Ba_Fir), Percent Basal Area Spruce (Pers_Ba_Sp), Percent Basal Area Fir Plus Percent Basel Area Spruce (Pers_Ba_Fir/Spr), Average Basal Area Per Fir and Spruce (Ave_Ba_Per_F/S), Percent Basal Area Aspen (Pers_Ba_Asp), Average Basal Area Per Aspen (Ave_Ba_Per_Asp). The implicit variables were then input into Microsoft Excel and normalized to positive values between 0 and 1 (see appendix B). This

normalization was conducted due to data input preferences of the NN. These normalized values were then used as input into the NN and LRM.

4.20 Statistical Analysis and Linear Regression Models (LRM)

This section outlines the methods and methodology used for the statistical analysis, construction and testing of the linear regression models, including (Section 4.21) descriptive statistics, (Section 4.22) correlation analyses, (Section 4.23) stepwise and hierarchical linear regression models

4.21 Descriptive Statistics

Descriptive statistics were compiled on the biophysical data using a computer statistical software package to determine levels of variability in the biophysical data across the 44 sampled stands. This output was then used to determine if biophysical factors (independent variables) across stands possessed enough variability to potentially be significant predictors of SBEs (dependent variable).

4.22 Correlation Analysis

A correlation analysis was conducted using the entire population of 44 stands and the 27 variables extracted from RMSTAND along with the SBE output from RMRATE.

This correlation analysis used SPSS, to determine which biophysical variables correlated the most with SBE's. The entire data set was then divided into two random groups three times using a random number generator. Random sets of 30 stands were used to construct the individual HLRM's for each group and the remaining sets of 14 were used to test the predictive capability of each HLRM. Correlation analyses were also run on each of the three sets of 30 and this information was used to determine input order for the HLRM's. Correlation analyses were also conducted for each set using the biophysical variables only, to determine if any covariance existed between them. The results from the correlation study were used to isolate potential variables for input into the HLRM's and NN's.

4.23 Stepwise and Hierarchical LRM

A stepwise linear regression, using SPSS, was run using all significant biophysical variables as independent variables and the SBE's as dependent variables, to determine which biophysical variables best explained the variance in the SBE values. This stepwise linear regression was run with the complete data using all 44 sample stands. This stepwise approach is used as a baseline for comparison with later HLRMs. A number of hierarchical linear regression models were then constructed and tested on each of the three groups to determine the most conclusive hierarchical linear regression model for predicting near view scenic beauty for each group.

Once the best HLRM was constructed for each of the three groups the resulting regression equation was tested using the test groups for each group. A number of NN's

were then constructed, mirroring the above mentioned HLRM's for each group and the results were compared between the expected SBE's and the predicted SBE's from the HLRM's and the NN's.

4.30 Neural Networks (NN)

This section outlines the methods and methodology used for the construction, testing and analysis of the neural network models, including (Section 4.31) NN Construction and Testing.

4.31 NN Construction and Testing

Back propagating NN's were constructed and trained using NeuralWare, a Unix based NN software program. Research in this field, (Gimblett, 1994; Gimblett, 1995; Bishop, 1996) provides strong evidence that a back propagating neural network with a delta learning rule and a sigmoid transfer function is the most efficient and optimal model architecture for this type of application (Gimblett, 1994; Gimblett, 1995; Bishop, 1996). The NN's constructed in this research mimiced this architecture. The first NN constructed used all biophysical variables as input nodes and the SBE as the output node. This NN was constructed for comparison with the stepwise linear regression model. A series of NNs were then constructed and tested, mirroring the structure of the best HLRM's for each group. From this series of NN's, the two model architectures with the highest

predictive capability were trained and tested on the 3 groups of data. The hidden layer was first constructed with 5 nodes in a single hidden layer and then variable numbers of hidden layer nodes and hidden layers were added and subtracted in an effort to construct the best NN for predicting SBE's

NN Model 1:

The NN model architecture for Model 1 consisted of 4 input nodes, 5 nodes in the hidden layer and 1 output node. The 4 input nodes represented the 4 significant variables from the HLRM for group 1. The single output node represented the dependent variable from the HLRM's, in this case SBE.

NN Model 2:

The NN model architecture for Model 2 consisted of 4 input nodes, 6 nodes in hidden layer 1 and 6 nodes in hidden layer 2 and 1 output node. The 4 input nodes represented the 4 significant variables from the HLRM for group 2. The single output node represented the dependent variable from the HLRM's, in this case SBE.

Each NN was trained on the set of 30 stands from each group, and once trained, was tested on the remaining set of 14 stands to determine its capability for predicting SBE. The predicted output (SBE) for each group was compared, via a correlation analysis, to the expected SBE value. The correlation coefficients for the two NN's were then averaged to produce a mean coefficient for each group. This correlation coefficient was compared, by group, to the correlation coefficient for the HLRM's to determine which method was a better predictor of SBE.

4.40 Model Comparisons

4.41 SBE Predictions of NN versus HLRM

The predictive capability of the NNs and the hierarchical LRM were compared to determine which, if either, was a better predictor of near view scenic beauty. The HLRMs were tested against the NN by comparing the predicted SBEs from each model with the expected SBEs from each model. This comparison was conducted between the HLRMs and the NN for each group.

This comparison consisted of a correlation analysis, by group, between the predicted SBE values and the expected SBE values for each method. The correlation coefficient for each group, by method, was compared to determine which method, if either, has a better correlation between predicted and expected SBE values.

5.0 Research Results

5.10 Linear Regression Models

This section discusses the research results of the statistical section of this research, including: descriptive statistics (Section 5.11), correlation analysis (Section 5.12), significant independent variables (Section 5.13), and HLRM construction and prediction (Section 5.14).

5.11 Descriptive Statisitics

Descriptive statistics were run the 15 explicit biophysical variables and SBE to determine their general levels of variability. A frequency distribution was charted for each variable and then graphed under the normal curve (see figure 3 to figure 18).

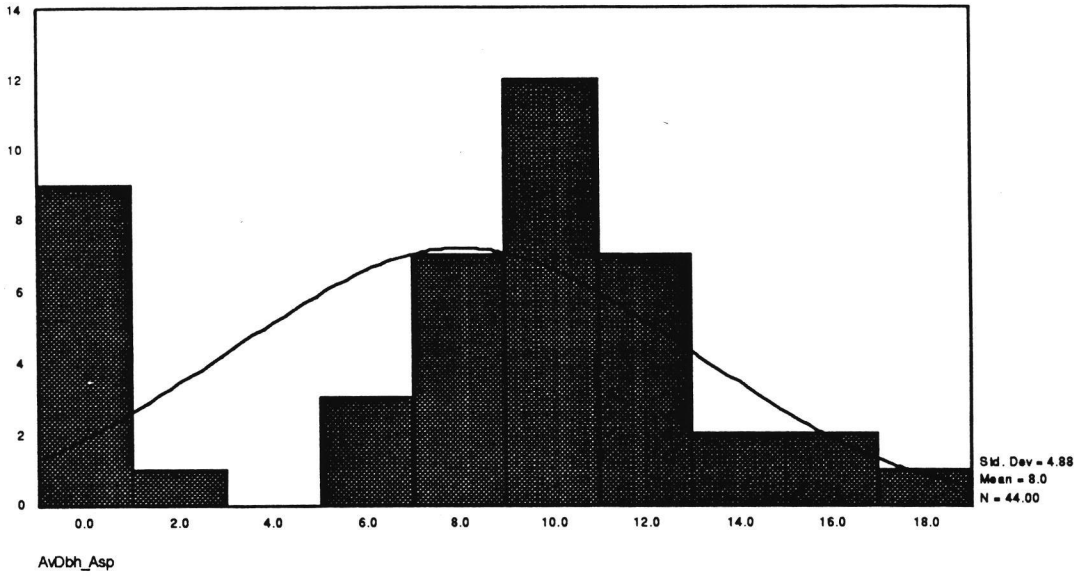

Figure 3. Descriptive Statistics, Average DBH Aspen

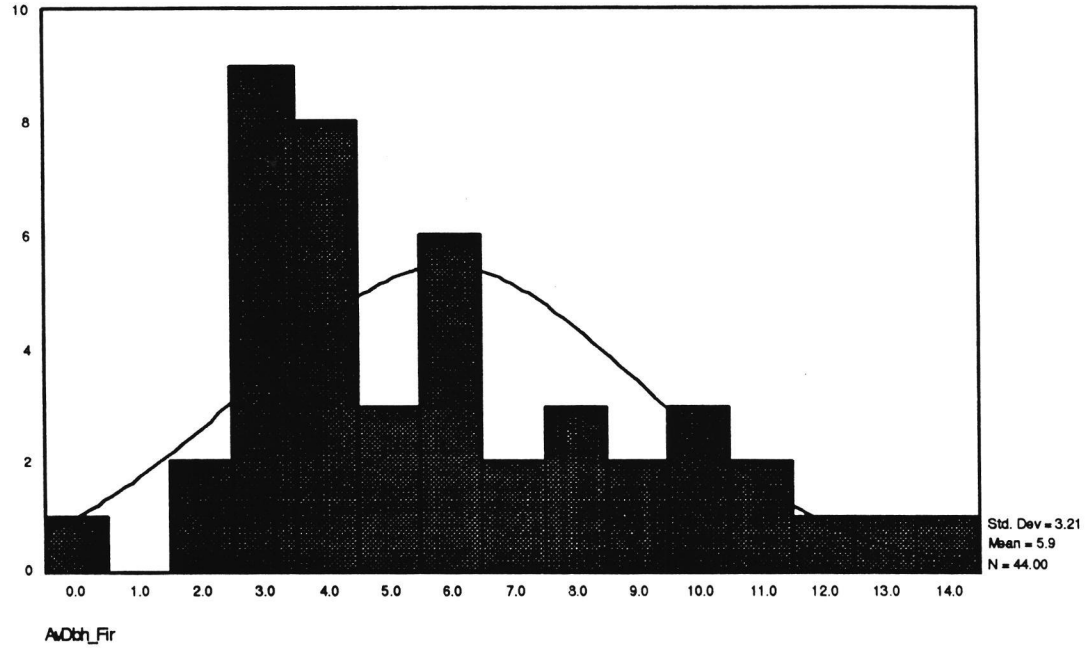

Figure 4. Descriptive Statistics, Average DBH Fir

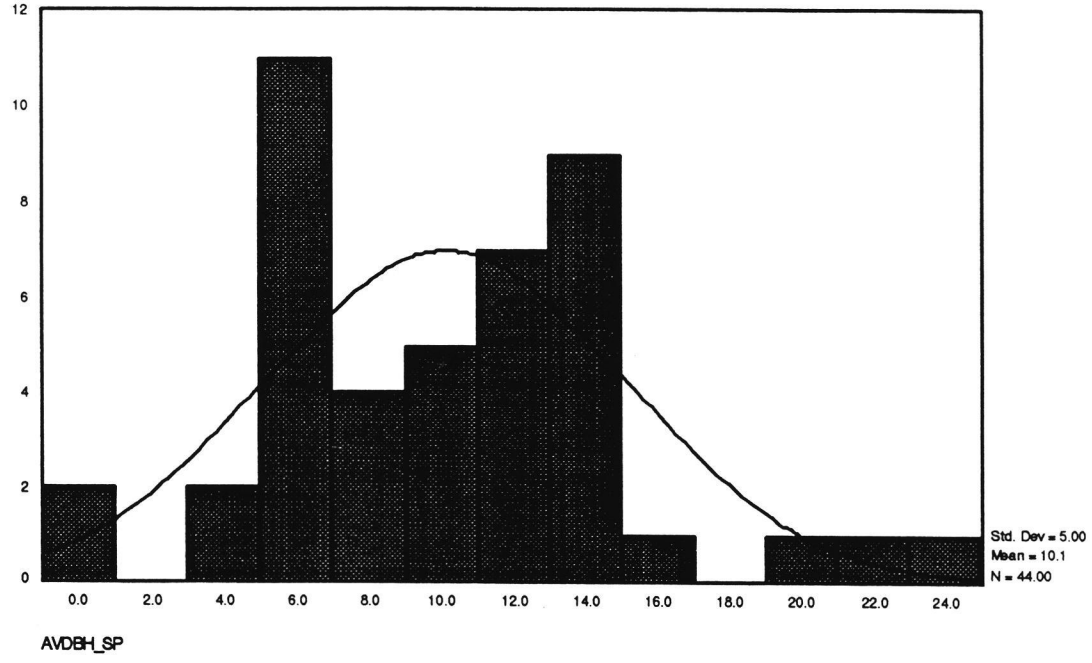

Figure 5. Descriptive Statisitics, Average DBH Spruce

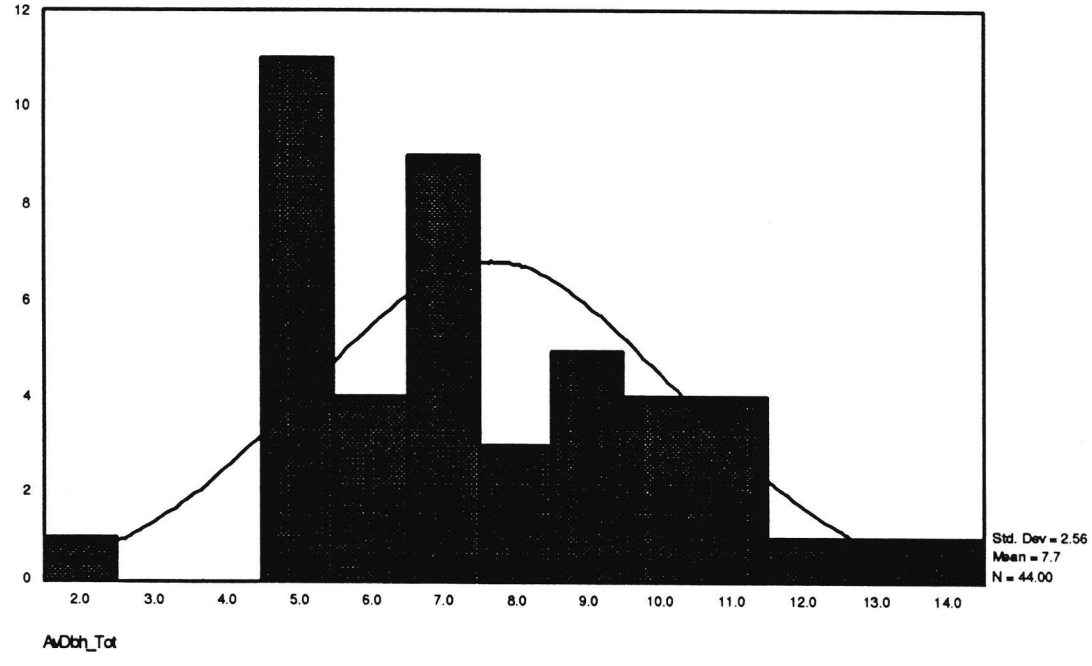

Figure 6. Descriptive Statisitics, Average DBH Total

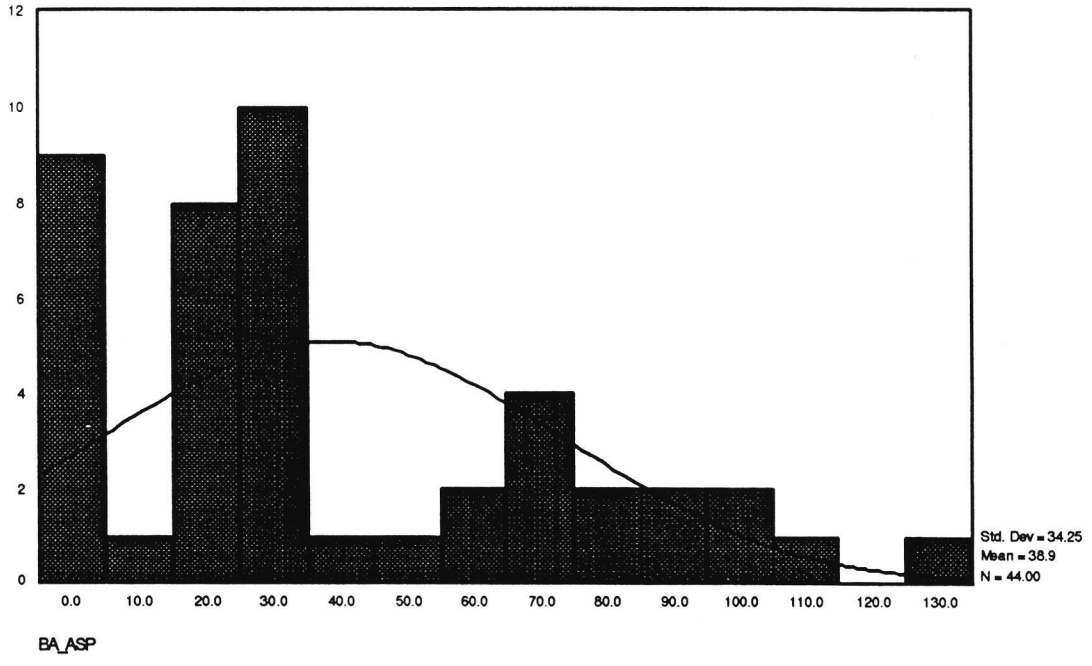

Figure 7. Descriptive Statistics, Basal Area Aspen

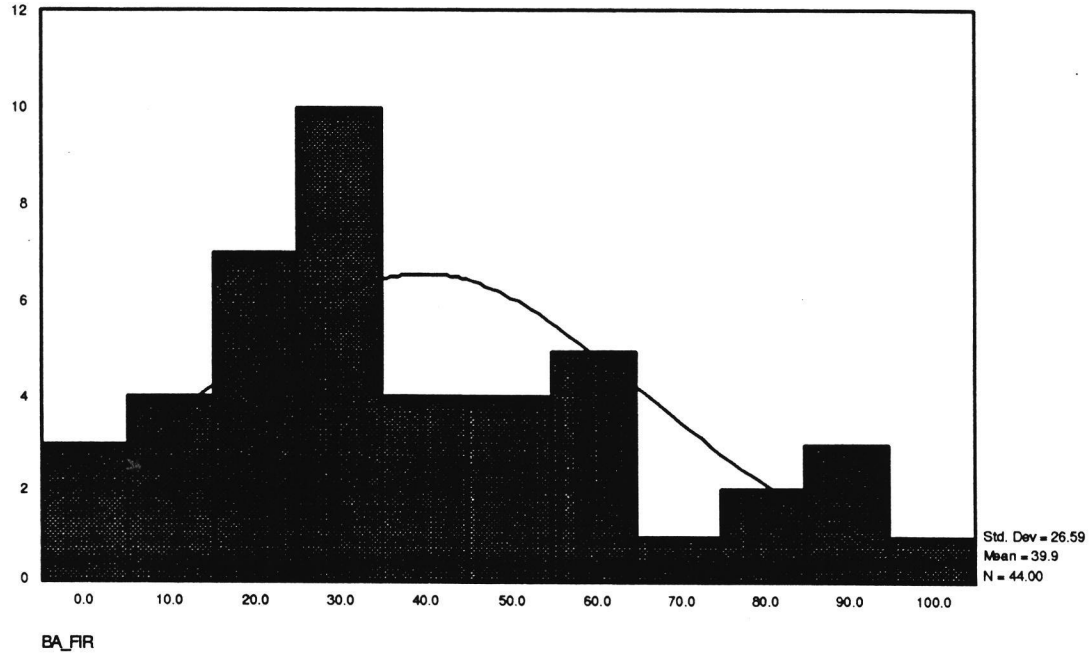

Figure 8. Descriptive Statistics, Basal Area Fir

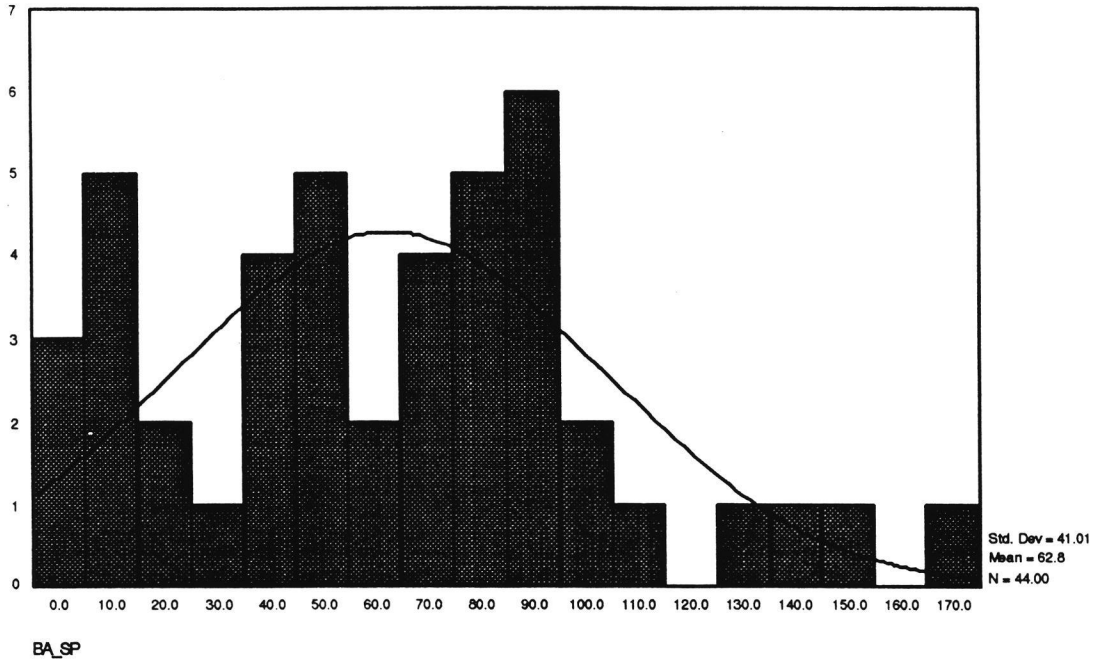

Figure 9. Descriptive Statisitics, Basal Area Spruce

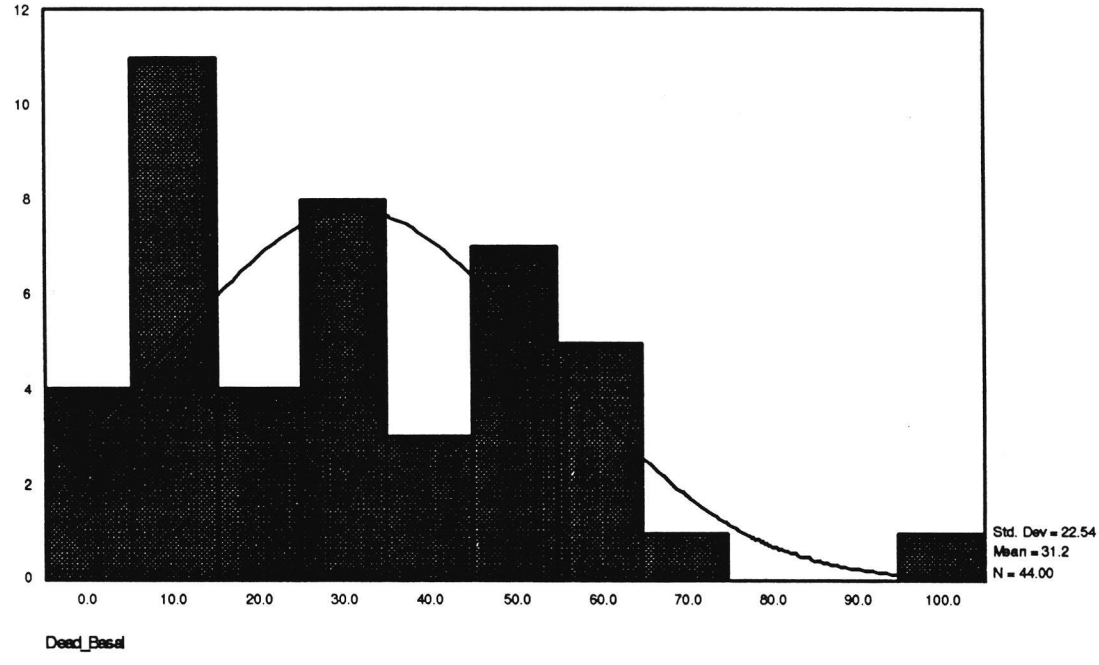

Figure 10. Descriptive Statistics, Dead Basal

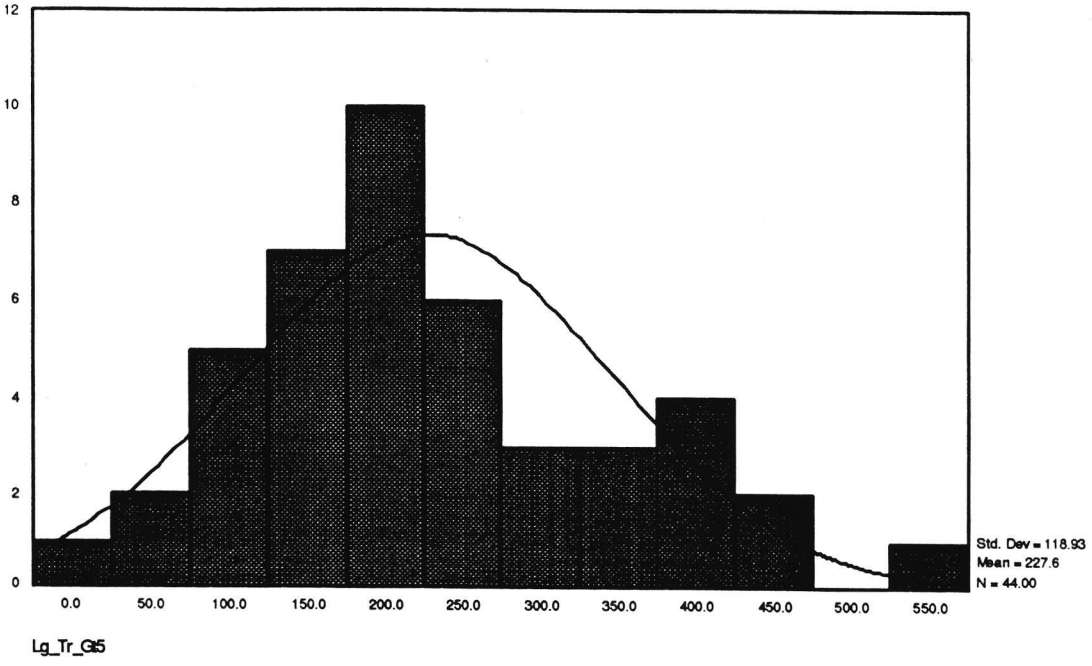

Figure 11. Descriptive Statistics, Large Trees Greater Than 5" Diameter

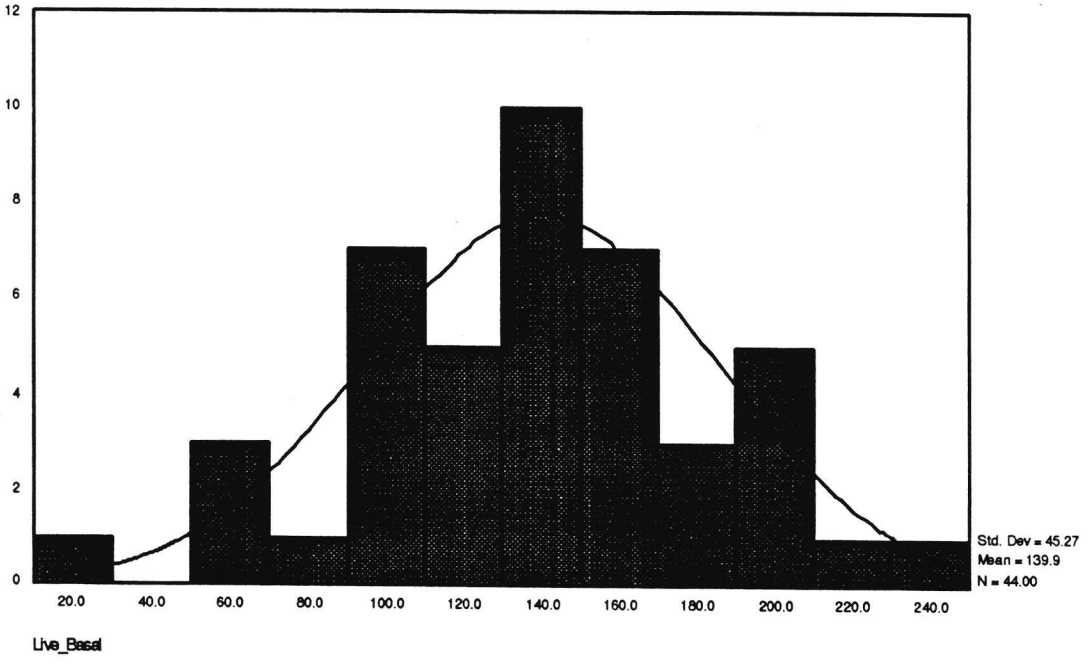

Figure 12. Descriptive Statistics, Live Basal Area

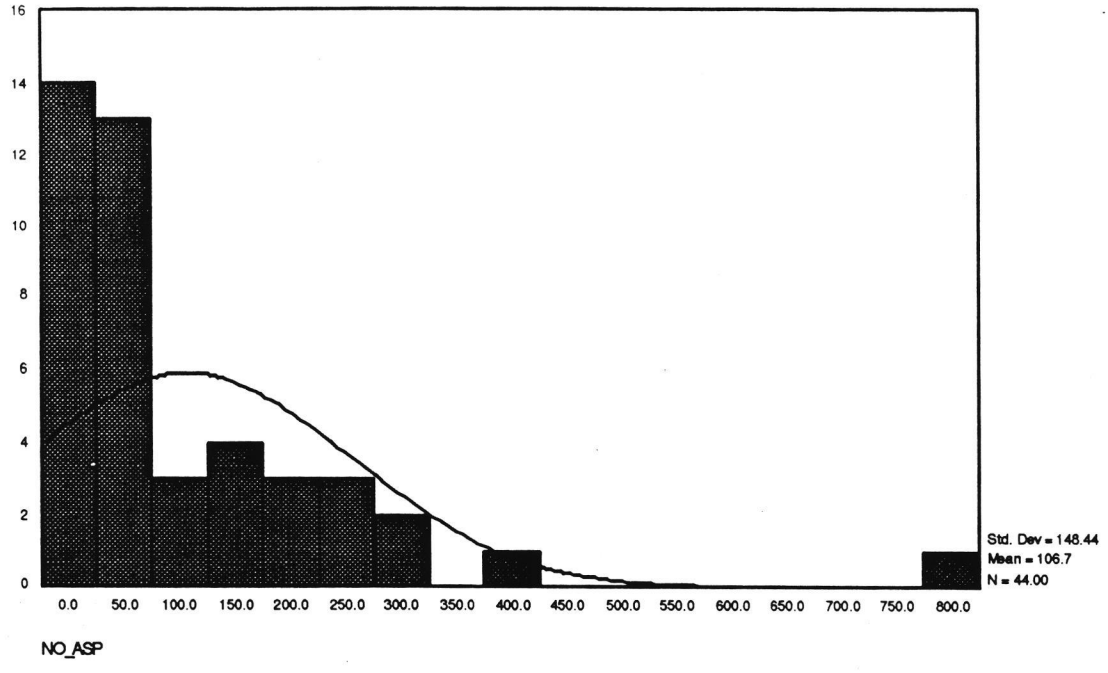

Figure 13. Descriptive Statistics, Number of Aspen Trees

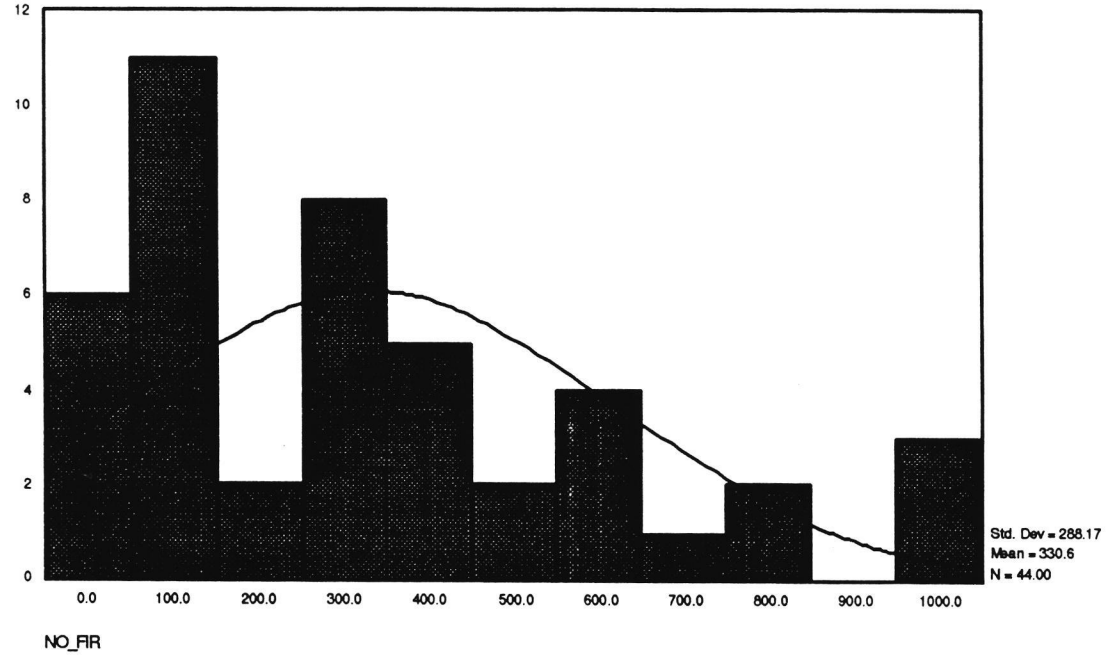

Figure 14. Descriptive Statistics, Number of Fir Trees

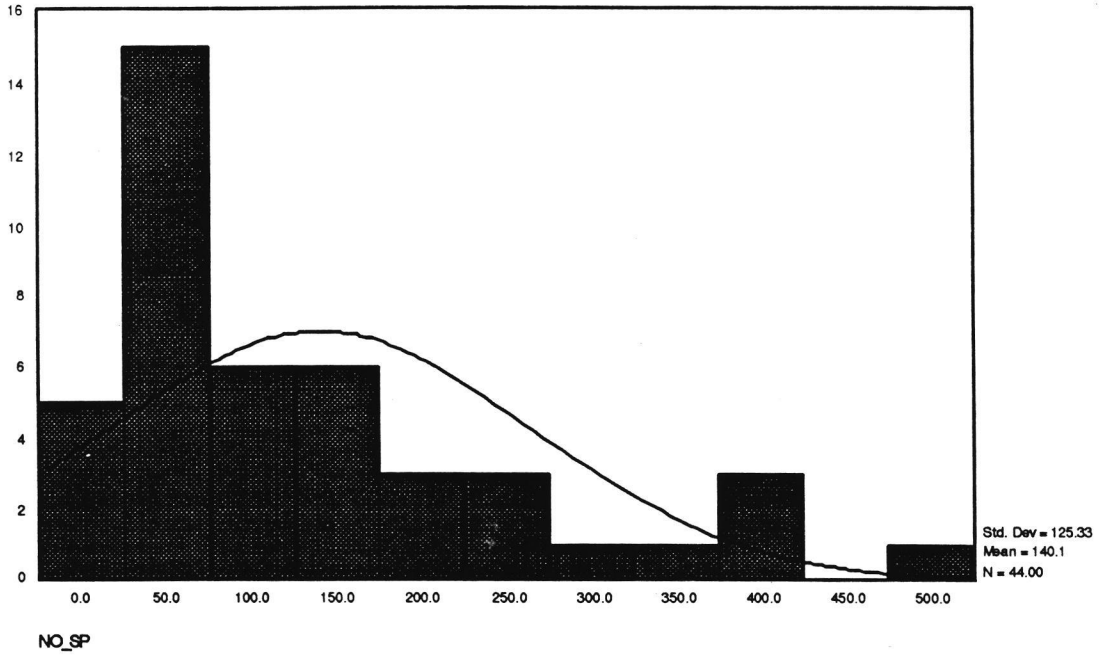

Figure 15. Descriptive Statistics, Number of Spruce Trees

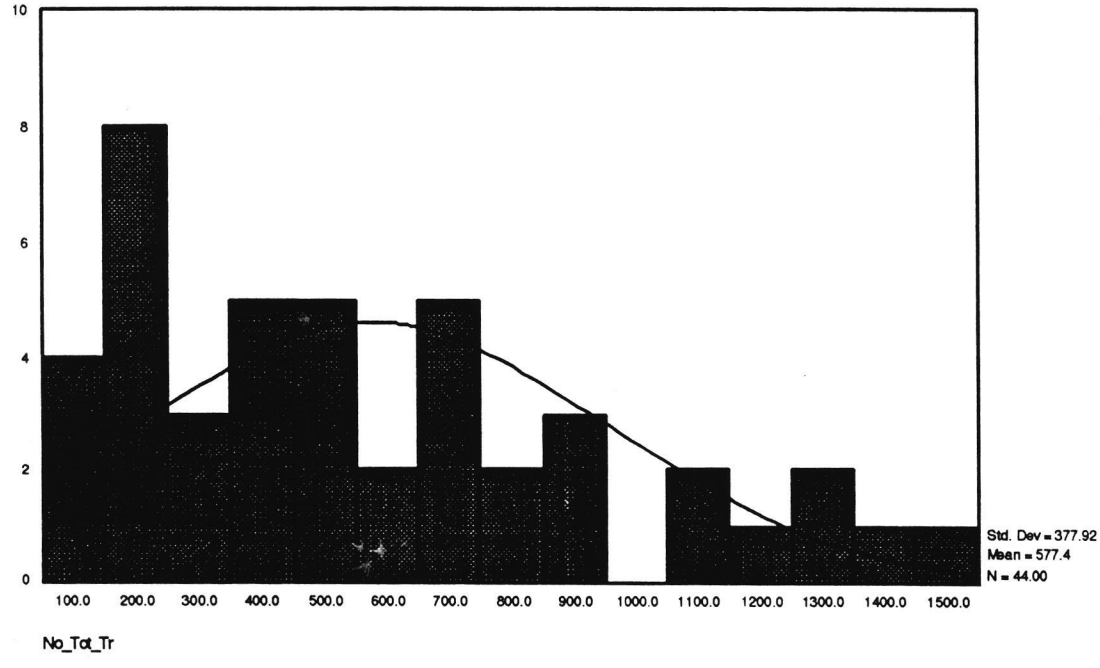

Figure 16. Descriptive Statistics, Number of Total Trees

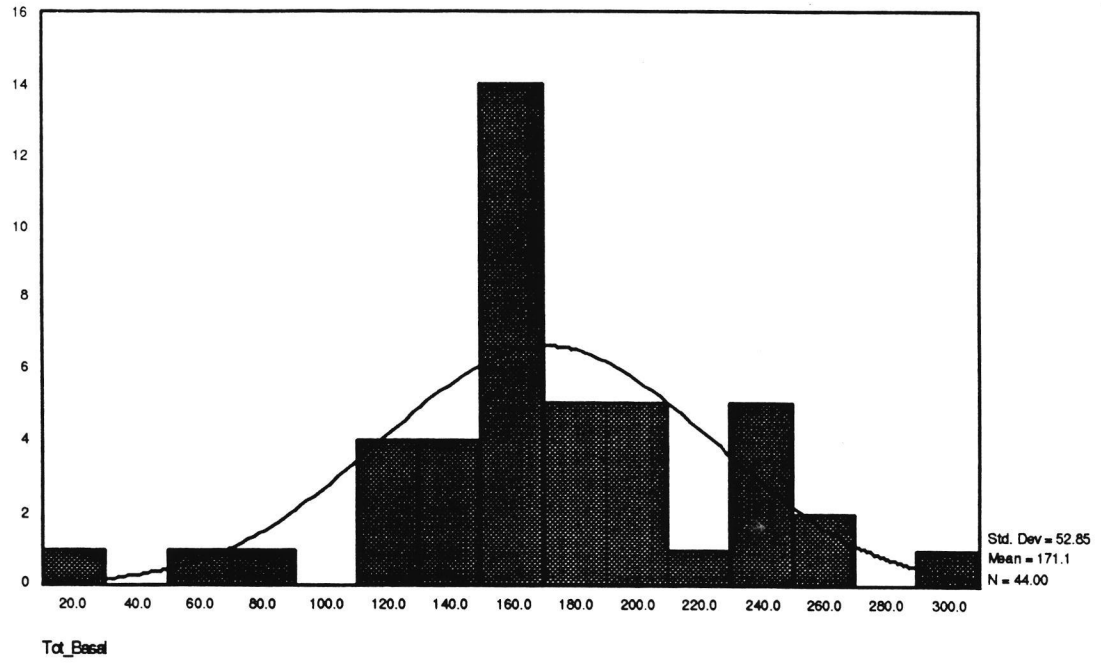

Figure 17. Descriptive Statistics, Total Basal Area

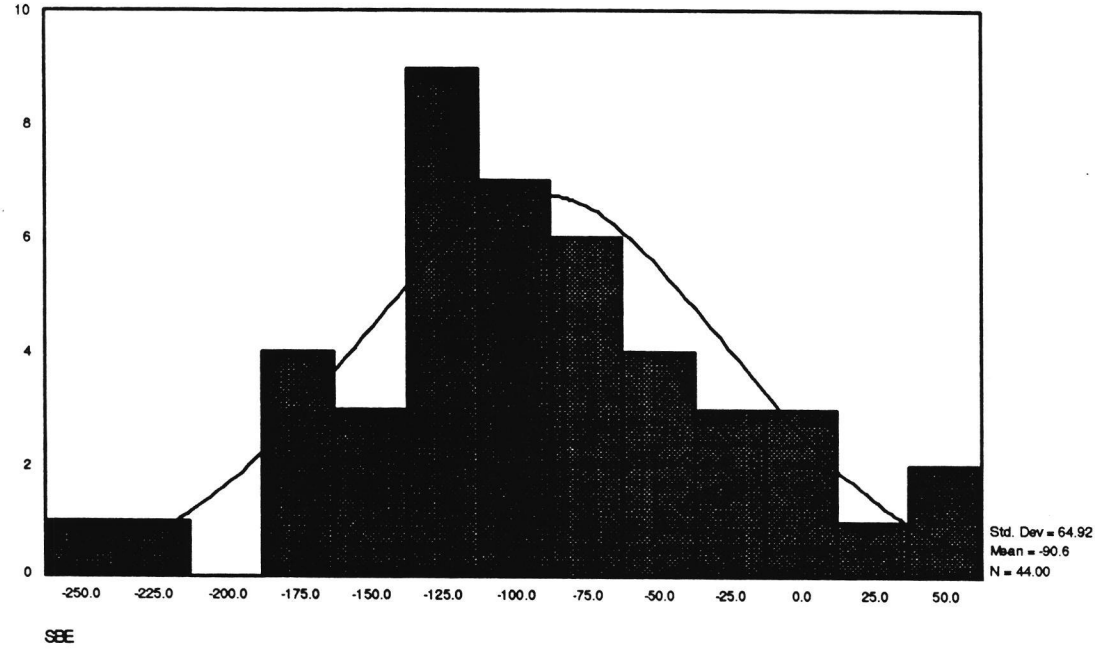

Figure 18. Descriptive Statistics, Scenic Beauty Estimates

The descriptive statistics reveal that most of the biophysical variables were normally distributed with a few exceptions. No biophysical variables were excluded as potential independent variables for further analysis based on the above descriptive statistics. It should be noted at this point that SBE was normally distributed (see Figure 18).

5.12 Correlation Analysis Entire Sample

An initial correlation analysis was conducted on all 27 biophysical variables and SBE's to determine which biophysical variables were highly correlated with SBE (see figure 19). This initial correlation was run on the entire sample of 44 stands. The results indicated that of the 27 biophysical variables 11 were significant, with P values at or below .05 and possessing high positive or negative correlation coefficients (see Figure 19).

	A_B_P_AS	AV_B_PFS	AVDBH_AS	AVDBH_FIR	AVDBH_SP	A_D_TOT
SBE_NORM	0.1664	-0.1844	0.2703	-0.1103	-0.2437	-0.2004
	44	44	44	44	44	44
	P = .286	P =.231	P = .076	P = .476	P = .111	P = .192

	AVE_BASAL	BA_ASP	BA_FIR	BA_SP	DEAD_BAS	LG_TR_GT5
SBE_NORM	-0.206	0.512	-0.0868	-0.3642	-0.2757	0.0739
	44	44	44	44	44	44
	P = .180	P = .000	P = .575	P = .015	P = .070	P = .634

	LIVE_BASAL	NO_ASP	NO_F_S	NO_FIR	NO_SP	NO_TOT_T
SBE_NORM	-0.0199	0.288	0.0522	0.0638	0.0002	0.1618
	44	44	44	44	44	44
	P = .898	P = .058	P = .736	P = .681	P = .999	P = .294

	P_AS_TR	P_B_FIR	P_BA_ASP	P_F_P_S	P_FIR_TR	PER_SP_T
SBE_NORM	0.3449	-0.0086	0.5546	-0.3447	-0.0205	-0.3009
	44	44	44	44	44	44
	P = .022	P = .956	P = .000	P = .022	P = .895	P = .047

	PR_B_FS	PR_B_SP	TOT_BASA
SBE_NORM	-0.3615	-0.3187	-0.1344
	44	44	44
	P = .016	P = .035	P = .384

Figure 19. Correlation Analysis, Biophysical Variables and SBE

These variables included, in order of highest to lowest significance: (1) percent basal area aspen, (2) basal area aspen, (3) basal area spruce, (4) percent basal area fir + percent basal area spruce, (5) percent aspen trees, (6) percent fir trees + percent spruce trees, (7) percent basal area spruce, (8) percent spruce trees, (9) number of aspen, (10) dead basal area, (11) average diameter breast height aspen. Correlation analyses were run on the above 11 biophysical variables (see figures 20 and 21), to determine if covariance exists between them.

	AVDBH_AS	BA_ASP	BA_SP	DEAD_BAS	NO_ASP	P_A_T
AVDBH_AS	1	0.3742	-0.3652	0.128	-0.0663	0.0426
	-44	-44	-44	-44	-44	-44
	P= .	P= .012	P= .015	P= .408	P= .669	P= .783
BA_ASP	0.3742	1	-0.5859	-0.008	0.5154	0.5722
	-44	-44	-44	-44	-44	-44
	P= .012	P= .	P= .000	P= .959	P= .000	P= .000
BA_SP	-0.3652	-0.5859	1	-0.0675	-0.5073	-0.6185
	-44	-44	-44	-44	-44	-44
	P= .015	P= .000	P= .	P= .663	P= .000	P= .000
DEAD_BAS	0.128	-0.008	-0.0675	1	-0.1224	-0.2825
	-44	-44	-44	-44	-44	-44
	P= .408	P= .959	P= .663	P= .	P= .428	P= .063
NO_ASP	-0.0663	0.5154	-0.5073	-0.1224	1	0.8143
	-44	-44	-44	-44	-44	-44
	P= .669	P= .000	P= .000	P= .428	P= .	P= .000
P_A_T	0.0426	0.5722	-0.6185	-0.2825	0.8143	1
	-44	-44	-44	-44	-44	-44
	P= .783	P= .000	P= .000	P= .063	P= .000	P= .
P_BA_ASP	0.2408	0.7587	-0.7091	-0.3073	0.8273	0.8625
	-44	-44	-44	-44	-44	-44
	P= .115	P= .000	P= .000	P= .042	P= .000	P= .000
P_F_P_S	-0.0428	-0.5722	0.6187	0.2823	-0.8142	-1
	-44	-44	-44	-44	-44	-44
	P= .783	P= .000	P= .000	P= .063	P= .000	P= .000
PER_SP_T	-0.405	-0.5212	0.6117	-0.1341	-0.4467	-0.4833
	-44	-44	-44	-44	-44	-44
	P= .006	P= .000	P= .000	P= .386	P= .002	P= .001
P_B_FS	-0.3363	-0.6809	0.8559	-0.1805	-0.7065	-0.7067
	-44	-44	-44	-44	-44	-44
	P= .026	P= .000	P= .000	P= .241	P= .000	P= .000
P_B_S	-0.4189	-0.6682	0.8896	-0.2096	-0.5662	-0.6157
	-44	-44	-44	-44	-44	-44
	P= .005	P= .000	P= .000	P= .172	P= .000	P= .000

Figure 20. Correlation Analysis, 11 Significant Variables

	P_BA_ASP	P_F_P_S	PER_SP_T	P_B_FS	P_B_S
AVDBH_AS	0.2408	-0.0428	-0.405	-0.3363	-0.4189
	-44	-44	-44	-44	-44
	P= .115	P= .783	P= .006	P= .026	P= .005
BA_ASP	0.7587	-0.5722	-0.5212	-0.6809	-0.6682
	-44	-44	-44	-44	-44
	P= .000	P= .000	P= .000	P= .000	P= .000
BA_SP	-0.7091	0.6187	0.6117	0.8559	0.8896
	-44	-44	-44	-44	-44
	P= .000	P= .000	P= .000	P= .000	P= .000
DEAD_BAS	-0.3073	0.2823	-0.1341	-0.1805	-0.2096
	-44	-44	-44	-44	-44
	P= .042	P= .063	P= .386	P= .241	P= .172
NO_ASP	0.8273	-0.8142	-0.4467	-0.7065	-0.5662
	-44	-44	-44	-44	-44
	P= .000	P= .000	P= .002	P= .000	P= .000
P_A_T	0.8625	-1	-0.4833	-0.7067	-0.6157
	-44	-44	-44	-44	-44
	P= .000	P= .000	P= .001	P= .000	P= .000
P_BA_ASP	1	-0.8625	-0.5307	-0.8209	-0.6998
	-44	-44	-44	-44	-44
	P= .	P= .000	P= .000	P= .000	P= .000
P_F_P_S	-0.8625	1	0.4834	0.7069	0.616
	-44	-44	-44	-44	-44
	P= .000	P= .	P= .001	P= .000	P= .000
PER_SP_T	-0.5307	0.4834	1	0.6419	0.7802
	-44	-44	-44	-44	-44
	P= .000	P= .001	P= .	P= .000	P= .000
P_B_FS	-0.8209	0.7069	0.6419	1	0.8802
	-44	-44	-44	-44	-44
	P= .000	P= .000	P= .000	P= .	P= .000
P_B_S	-0.6998	0.616	0.7802	0.8802	1
	-44	-44	-44	-44	-44

Figure 21. Correlation Analysis, 11 Significant Variables - continued

This second correlation analysis revealed that in many cases there were high correlation coefficients between many of the significant variables. Understanding that this may lead to inflated multiple R and adjusted R values in the HLRM's, all covariant variables resulting from the stepwise linear regression were included in the HLRM. This provided the opportunity to test the ability of NN's to handle situations with high correlation between input nodes. This same method of teasing out significant variables, and then testing for covariance was also used independently on each of the three random groups of data.

After randomly dividing the 44 samples into three groups of 30 and 14, as described in section 4.11 (Correlation Analysis), correlation analyses were conducted on each group to determine significant correlation between biophysical variables and SBE. A correlation was then conducted on the significant variables for each group to determine levels of covariance.

5.13 Significant Independent Variables by Group

GROUP 1.

The initial correlation on group 1 revealed 8 significant variables including, in order of significance: (1) percent basal area aspen, (2) basal area aspen, (3) percent aspen trees, (4) percent spruce trees + percent fir trees, (5) number of aspen, (6) dead basal, (7) basal area spruce, (8) percent basal area fir + percent basal area spruce (see figures 22, 23, 24). The correlation conducted between significant variables had similar results as the second correlation on the entire sample where high correlation coefficients were shown to exist (see figures 25, 26).

	P_F_T	PER_SP_T	SBE_NORM	TOT_BAS
A_B_P_AS	0.5831	-0.2746	0.0818	0.0314
	-30	-30	-30	-30
	P= .001	P= .142	P= .667	P= .869
A_B_PFS	-0.375	0.316	-0.1528	-0.0776
	-30	-30	-30	-30
	P= .041	P= .089	P= .420	P= .684
AVDBH_AS	0.5101	-0.5114	0.2562	0.0908
	-30	-30	-30	-30
	P= .004	P= .004	P= .172	P= .633
AVDBH_FI	-0.4601	0.3304	0.0068	-0.0713
	-30	-30	-30	-30
	P= .011	P= .075	P= .971	P= .708
AVDBH_SP	0.2779	-0.0719	-0.3124	0.0935
	-30	-30	-30	-30
	P= .137	P= .706	P= .093	P= .623
AVDBH_TO	-0.2172	0.3327	-0.1788	-0.015
	-30	-30	-30	-30
	P= .249	P= .072	P= .345	P= .937
AVE_BASE	-0.2804	0.3575	-0.1861	-0.0728
	-30	-30	-30	-30
	P= .133	P= .052	P= .325	P= .702
BA_ASP	0.0436	-0.5478	0.5688	0.4018
	-30	-30	-30	-30
	P= .819	P= .002	P= .001	P= .028
BA_FIR	0.5313	-0.4509	-0.0664	0.6487
	-30	-30	-30	-30
	P= .003	P= .012	P= .727	P= .000
BA_SP	-0.0238	0.6433	-0.3779	0.1675
	-30	-30	-30	-30
	P= .901	P= .000	P= .040	P= .376
DEAD_BAS	0.4166	-0.062	-0.3853	0.6458
	-30	-30	-30	-30
	P= .022	P= .745	P= .035	P= .000

Figure 22. Correlation Analysis, Gr1 All Variables

	P F T	PER SP T	SBE NORM	TOT BAS
LG TR GT	0.2932	-0.3014	0.1562	0.7802
	-30	-30	-30	-30
	P= .116	P= .106	P= .410	P= .000
LIVE BAS	0.3949	-0.215	0.0538	0.9151
	-30	-30	-30	-30
	P= .031	P= .254	P= .778	P= .000
NO ASP	-0.3482	-0.4574	0.3885	-0.1905
	-30	-30	-30	-30
	P= .059	P= .011	P= .034	P= .313
NO F S	0.5477	-0.1323	0.0201	0.5753
	-30	-30	-30	-30
	P= .002	P= .486	P= .916	P= .001
NO FIR	0.7074	-0.388	0.0167	0.623
	-30	-30	-30	-30
	P= .000	P= .034	P= .930	P= .000
NO SP	-0.1481	0.5459	0.0163	0.1265
	-30	-30	-30	-30
	P= .435	P= .002	P= .932	P= .505
NO TOT T	0.3665	-0.3237	0.1877	0.4609
	-30	-30	-30	-30
	P= .046	P= .081	P= .321	P= .010
P A T	-0.4505	-0.5276	0.4178	-0.2808
	-30	-30	-30	-30
	P= .012	P= .003	P= .022	P= .133
P B F	0.5209	-0.4824	0.0197	0.3166
	-30	-30	-30	-30
	P= .003	P= .007	P= .918	P= .088
P B FS	0.0408	0.6612	-0.36	0.011
	-30	-30	-30	-30
	P= .831	P= .000	P= .051	P= .954
P B S	-0.201	0.7903	-0.3201	-0.1341
	-30	-30	-30	-30
	P= .287	P= .000	P= .085	P= .480

Figure 23. Correlation Analysis, Gr1 All Variables - continued

	P_F_T	PER_SP_T	SBE_NORM	TOT_BAS
P_BA_ASP	-0.2835	-0.5674	0.6121	-0.202
	-30	-30	-30	-30
	P= .129	P= .001	P= .000	P= .284
P_F_P_S	0.4504	0.5277	-0.4175	0.2807
	-30	-30	-30	-30
	P= .013	P= .003	P= .022	P= .133
P_F_T	1	-0.5207	-0.1461	0.4896
	-30	-30	-30	-30
	P= .	P= .003	P= .441	P= .006
PER_SP_T	-0.5207	1	-0.2602	-0.1973
	-30	-30	-30	-30
	P= .003	P= .	P= .165	P= .296
SBE_NORM	-0.1461	-0.2602	1	-0.119
	-30	-30	-30	-30
	P= .441	P= .165	P= .	P= .531
TOT_BAS	0.4896	-0.1973	-0.119	1
	-30	-30	-30	-30
	P= .006	P= .296	P= .531	P= .

Figure 24. Correlation Analysis, Gr1 All Variables - continued

	P_BA_ASP	BA_ASP	P_A_T	P_F_P_S
P_BA_ASP	1	0.7197	0.8755	-0.8754
	-30	-30	-30	-30
	P= .	P= .000	P= .000	P= .000
BA_ASP	0.7197	1	0.5296	-0.5295
	-30	-30	-30	-30
	P= .000	P= .	P= .003	P= .003
P_A_T	0.8755	0.5296	1	-1
	-30	-30	-30	-30
	P= .000	P= .003	P= .	P= .000
P_F_P_S	-0.8754	-0.5295	-1	1
	-30	-30	-30	-30
	P= .000	P= .003	P= .000	P= .
NO_ASP	0.8679	0.4575	0.8248	-0.8247
	-30	-30	-30	-30
	P= .000	P= .011	P= .000	P= .000
DEAD_BAS	-0.3669	-0.0139	-0.3499	0.3496
	-30	-30	-30	-30
	P= .046	P= .942	P= .058	P= .058
BA_SP	-0.7352	-0.6061	-0.6489	0.6491
	-30	-30	-30	-30
	P= .000	P= .000	P= .000	P= .000
P_B_FS	-0.8384	-0.6727	-0.7318	0.732
	-30	-30	-30	-30
	P= .000	P= .000	P= .000	P= .000

Figure 25. Correlation Analysis, Gr1 Significant Variables

	BA_SP	P_B_FS	NO_ASP	DEAD_BAS
P_BA_ASP	-0.7352	-0.8384	0.8679	-0.3669
	-30	-30	-30	-30
	P= .000	P= .000	P= .000	P= .046
BA_ASP	-0.6061	-0.6727	0.4575	-0.0139
	-30	-30	-30	-30
	P= .000	P= .000	P= .011	P= .942
P_A_T	-0.6489	-0.7318	0.8248	-0.3499
	-30	-30	-30	-30
	P= .000	P= .000	P= .000	P= .058
P_F_P_S	0.6491	0.732	-0.8247	0.3496
	-30	-30	-30	-30
	P= .000	P= .000	P= .000	P= .058
NO_ASP	-0.5311	-0.736	1	-0.2229
	-30	-30	-30	-30
	P= .003	P= .000	P= .	P= .236
DEAD_BAS	0.067	-0.0862	-0.2229	1
	-30	-30	-30	-30
	P= .725	P= .651	P= .236	P= .
BA_SP	1	0.8422	-0.5311	0.067
	-30	-30	-30	-30
	P= .	P= .000	P= .003	P= .725
P_B_FS	0.8422	1	-0.736	-0.0862
	-30	-30	-30	-30
	P= .000	P= .	P= .000	P= .651

Figure 26. Correlation Analysis, Gr1 Significant Variables - continued

GROUP 2.

The initial correlation on group 2 revealed 9 significant variables including, in order of significance: (1) basal area aspen, (2) percent basal area aspen, (3) basal area spruce + percent basal area fir, (4) percent basal area spruce, (5) basal area spruce , (6)

percent spruce trees, (7) percent aspen trees , (8) percent fir trees + percent spruce trees, (9) average basal area all trees (see figures 27, 28, 29). The correlation conducted between significant variables had similar results as the second correlation on the entire sample where high correlation coefficients were shown to exist (see figures 30,31).

	P_F_T	PER_SP_T	SBE_NORM	TOT_BAS
A_B_P_AS	0.5539	-0.2128	0.165	0.1252
	-30	-30	-30	-30
	P= .001	P= .259	P= .384	P= .510
A_B_PFS	-0.3559	0.2548	-0.337	-0.0288
	-30	-30	-30	-30
	P= .054	P= .174	P= .069	P= .880
AVDBH_AS	0.4392	-0.402	0.3235	0.2117
	-30	-30	-30	-30
	P= .015	P= .028	P= .081	P= .261
AVDBH_FI	-0.4914	0.3549	-0.2172	-0.01
	-30	-30	-30	-30
	P= .006	P= .054	P= .249	P= .958
AVDBH_SP	0.2996	-0.0004	-0.3463	-0.0074
	-30	-30	-30	-30
	P= .108	P= .998	P= .061	P= .969
AVDBH_TO	-0.2422	0.3659	-0.3418	-0.0136
	-30	-30	-30	-30
	P= .197	P= .047	P= .065	P= .943
AVE_BASE	-0.2882	0.3701	-0.3596	-0.0481
	-30	-30	-30	-30
	P= .123	P= .044	P= .051	P= .801
BA_ASP	-0.0677	-0.4843	0.6126	0.3517
	-30	-30	-30	-30
	P= .722	P= .007	P= .000	P= .057
BA_FIR	0.3387	-0.2872	0.013	0.6336
	-30	-30	-30	-30
	P= .067	P= .124	P= .946	P= .000
BA_SP	0.083	0.5537	-0.5024	0.3869
	-30	-30	-30	-30
	P= .663	P= .002	P= .005	P= .035
DEAD_BAS	0.3791	-0.0608	-0.2186	0.5617
	-30	-30	-30	-30
	P= .039	P= .750	P= .246	P= .001

Figure 27. Correlation Analysis, Gr2 All Variables

	P F T	PER SP T	SBE NORM	TOT BAS
LG TR GT	0.1059	-0.1682	0.2028	0.6959
	-30	-30	-30	-30
	P= .578	P= .374	P= .282	P= .000
LIVE BAS	0.1878	-0.0264	0.0261	0.9017
	-30	-30	-30	-30
	P= .320	P= .890	P= .891	P= .000
NO ASP	-0.3787	-0.4335	0.3276	-0.1526
	-30	-30	-30	-30
	P= .039	P= .017	P= .077	P= .421
NO F S	0.4889	-0.1196	0.1603	0.6024
	-30	-30	-30	-30
	P= .006	P= .529	P= .398	P= .000
NO FIR	0.6578	-0.3625	0.1975	0.5984
	-30	-30	-30	-30
	P= .000	P= .049	P= .296	P= .000
NO SP	-0.1058	0.4822	0.0066	0.35
	-30	-30	-30	-30
	P= .578	P= .007	P= .973	P= .058
NO TOT T	0.3012	-0.291	0.2853	0.5008
	-30	-30	-30	-30
	P= .106	P= .119	P= .126	P= .005
P A T	-0.5053	-0.493	0.3698	-0.2761
	-30	-30	-30	-30
	P= .004	P= .006	P= .044	P= .140
P B F	0.3666	-0.3645	0.0702	0.2561
	-30	-30	-30	-30
	P= .046	P= .048	P= .712	P= .172
P B FS	0.1581	0.6077	-0.5452	0.1558
	-30	-30	-30	-30
	P= .404	P= .000	P= .002	P= .411
P B S	-0.0471	0.7242	-0.5187	0.0072
	-30	-30	-30	-30
	P= .805	P= .000	P= .003	P= .970

Figure 28. Correlation Analysis, Gr2 All Variables - continued

	P_F_T	PER_SP_T	SBE_NORM	TOT_BAS
P_BA_ASP	-0.3425	-0.5307	0.6077	-0.259
	-30	-30	-30	-30
	P= .064	P= .003	P= .000	P= .167
P_F_P_S	0.5053	0.493	-0.3696	0.276
	-30	-30	-30	-30
	P= .004	P= .006	P= .044	P= .140
P_F_T	1	-0.5017	0.0831	0.3229
	-30	-30	-30	-30
	P= .	P= .005	P= .662	P= .082
PER_SP_T	-0.5017	1	-0.4543	-0.0489
	-30	-30	-30	-30
	P= .005	P= .	P= .012	P= .798
SBE_NORM	0.0831	-0.4543	1	-0.0736
	-30	-30	-30	-30
	P= .662	P= .012	P= .	P= .699
TOT_BAS	0.3229	-0.0489	-0.0736	1
	-30	-30	-30	-30
	P= .082	P= .798	P= .699	P= .

Figure 29. Correlation Analysis, Gr2 All variables - continued

	BA_ASP	P_BA_ASP	P_B_FS	P_B_S	BA_SP
BA_ASP	1	0.703	-0.6489	-0.6409	-0.4836
	-30	-30	-30	-30	-30
	P= .	P= .000	P= .000	P= .000	P= .007
P_BA_ASP	0.703	1	-0.8619	-0.7232	-0.68
	-30	-30	-30	-30	-30
	P= .000	P= .	P= .000	P= .000	P= .000
P_B_FS	-0.6489	-0.8619	1	0.8603	0.8056
	-30	-30	-30	-30	-30
	P= .000	P= .000	P= .	P= .000	P= .000
P_B_S	-0.6409	-0.7232	0.8603	1	0.8755
	-30	-30	-30	-30	-30
	P= .000	P= .000	P= .000	P= .	P= .000
BA_SP	-0.4836	-0.68	0.8056	0.8755	1
	-30	-30	-30	-30	-30
	P= .007	P= .000	P= .000	P= .000	P= .
PER_SP_T	-0.4843	-0.5307	0.6077	0.7242	0.5537
	-30	-30	-30	-30	-30
	P= .007	P= .003	P= .000	P= .000	P= .002
P_A_T	0.5513	0.8739	-0.7652	-0.6749	-0.6358
	-30	-30	-30	-30	-30
	P= .002	P= .000	P= .000	P= .000	P= .000
P_F_P_S	-0.5512	-0.8738	0.7652	0.675	0.6358
	-30	-30	-30	-30	-30
	P= .002	P= .000	P= .000	P= .000	P= .000
AVE_BASE	-0.3194	-0.3716	0.4351	0.3577	0.2902
	-30	-30	-30	-30	-30
	P= .085	P= .043	P= .016	P= .052	P= .120

Figure 30. Correlation Analysis, Gr2 Significant Variables

	P_A_T	P_F_P_S	AVE_BASE	PER_SP_T
BA_ASP	0.5513	-0.5512	-0.3194	-0.4843
	-30	-30	-30	-30
	P= .002	P= .002	P= .085	P= .007
P_BA_ASP	0.8739	-0.8738	-0.3716	-0.5307
	-30	-30	-30	-30
	P= .000	P= .000	P= .043	P= .003
P_B_FS	-0.7652	0.7652	0.4351	0.6077
	-30	-30	-30	-30
	P= .000	P= .000	P= .016	P= .000
P_B_S	-0.6749	0.675	0.3577	0.7242
	-30	-30	-30	-30
	P= .000	P= .000	P= .052	P= .000
BA_SP	-0.6358	0.6358	0.2902	0.5537
	-30	-30	-30	-30
	P= .000	P= .000	P= .120	P= .002
PER_SP_T	-0.493	0.493	0.3701	1
	-30	-30	-30	-30
	P= .006	P= .006	P= .044	P= .
P_A_T	1	-1	-0.0795	-0.493
	-30	-30	-30	-30
	P= .	P= .000	P= .676	P= .006
P_F_P_S	-1	1	0.0794	0.493
	-30	-30	-30	-30
	P= .000	P= .	P= .677	P= .006
AVE_BASE	-0.0795	0.0794	1	0.3701
	-30	-30	-30	-30
	P= .676	P= .677	P= .	P= .044

Figure 31. Correlation Analysis, Gr2 Significant Variables - continued

GROUP 3.

The initial correlation on group 3 revealed 8 significant variables including, in order of significance: (1) percent basal area aspen, (2) basal area aspen, (3) basal area spruce, (4) percent aspen trees, (5) percent spruce trees + percent fir trees, (6) dead basal area, (7) percent basal area fir + percent basal area spruce, (8) percent basal area spruce (see figures 32, 33, 34). The correlation conducted between significant variables had similar results as the second correlation on the entire sample where high correlation coefficients were shown to exist (see figures 35, 36). The results of the correlation analyses for the three groups of data were used to construct HLRM's for each group.

	P_F_T	PER_SP_T	SBE_NORM	TOT_BAS
A_B_P_AS	0.36	-0.1215	0.1324	0.137
	-30	-30	-30	-30
	P= .051	P= .522	P= .486	P= .470
A_B_PFS	-0.4149	0.609	-0.1378	-0.1233
	-30	-30	-30	-30
	P= .023	P= .000	P= .468	P= .516
AVDBH_AS	0.2454	-0.267	0.2266	0.1689
	-30	-30	-30	-30
	P= .191	P= .154	P= .229	P= .372
AVDBH_FI	-0.521	0.5826	0.008	-0.0586
	-30	-30	-30	-30
	P= .003	P= .001	P= .967	P= .758
AVDBH_SP	0.3743	0.1432	-0.2369	0.0475
	-30	-30	-30	-30
	P= .042	P= .450	P= .208	P= .803
AVDBH_TO	-0.2769	0.5549	-0.1462	-0.0512
	-30	-30	-30	-30
	P= .139	P= .001	P= .441	P= .788
AVE_BASE	-0.3411	0.5956	-0.17	-0.1155
	-30	-30	-30	-30
	P= .065	P= .001	P= .369	P= .543
BA_ASP	0.0107	-0.5262	0.4604	0.2637
	-30	-30	-30	-30
	P= .955	P= .003	P= .010	P= .159
BA_FIR	0.4782	-0.3348	-0.0934	0.7806
	-30	-30	-30	-30
	P= .008	P= .071	P= .623	P= .000
BA_SP	-0.0436	0.6362	-0.4511	0.3381
	-30	-30	-30	-30
	P= .819	P= .000	P= .012	P= .068
DEAD_BAS	0.619	-0.1757	-0.3622	0.4313
	-30	-30	-30	-30
	P= .000	P= .353	P= .049	P= .017

Figure 32. Correlation Analysis, Gr3 All Variables

	P F T	PER SP T	SBE NORM	TOT BAS
LG TR GT	0.2558	-0.2461	0.024	0.7442
	-30	-30	-30	-30
	P= .173	P= .190	P= .900	P= .000
LIVE BAS	0.272	-0.0574	-0.1569	0.9332
	-30	-30	-30	-30
	P= .146	P= .763	P= .408	P= .000
NO ASP	-0.335	-0.4755	0.2357	-0.2105
	-30	-30	-30	-30
	P= .070	P= .008	P= .210	P= .264
NO F S	0.5668	-0.225	-0.1228	0.6375
	-30	-30	-30	-30
	P= .001	P= .232	P= .518	P= .000
NO FIR	0.6951	-0.4273	-0.0771	0.619
	-30	-30	-30	-30
	P= .000	P= .019	P= .686	P= .000
NO SP	-0.1053	0.4582	-0.1793	0.3296
	-30	-30	-30	-30
	P= .580	P= .011	P= .343	P= .075
NO TOT T	0.3694	-0.4154	-0.0079	0.4888
	-30	-30	-30	-30
	P= .045	P= .022	P= .967	P= .006
P A T	-0.4773	-0.49	0.3765	-0.3634
	-30	-30	-30	-30
	P= .008	P= .006	P= .040	P= .048
P B F	0.5048	-0.4513	0.0915	0.4829
	-30	-30	-30	-30
	P= .004	P= .012	P= .631	P= .007
P B FS	-0.0234	0.7111	-0.3572	0.2273
	-30	-30	-30	-30
	P= .902	P= .000	P= .053	P= .227
P B S	-0.2279	0.8192	-0.356	0.0046
	-30	-30	-30	-30
	P= .226	P= .000	P= .053	P= .981

Figure 33. Correlation Analysis, Gr3 All Variables - continued

	P_F_T	PER_SP_T	SBE_NORM	TOT_BAS
P_BA_ASP	-0.3203	-0.5425	0.5206	-0.3072
	-30	-30	-30	-30
	P= .084	P= .002	P= .003	P= .099
P_F_P_S	0.477	0.4903	-0.3764	0.3633
	-30	-30	-30	-30
	P= .008	P= .006	P= .040	P= .048
P_F_T	1	-0.5321	-0.0696	0.4694
	-30	-30	-30	-30
	P= .	P= .002	P= .715	P= .009
PER_SP_T	-0.5321	1	-0.2936	-0.1154
	-30	-30	-30	-30
	P= .002	P= .	P= .115	P= .544
SBE_NORM	-0.0696	-0.2936	1	-0.2723
	-30	-30	-30	-30
	P= .715	P= .115	P= .	P= .145
TOT_BAS	0.4694	-0.1154	-0.2723	1
	-30	-30	-30	-30
	P= .009	P= .544	P= .145	P= .

Figure 34. Correlation Analysis, Gr3 All Variables - continued

	P_BA_ASP	P_F_P_S	P_B_FS	BA_ASP
P_BA_ASP	1	-0.8929	-0.8367	0.7219
	-30	-30	-30	-30
	P= .	P= .000	P= .000	P= .000
P_F_P_S	-0.8929	1	0.7141	-0.5353
	-30	-30	-30	-30
	P= .000	P= .	P= .000	P= .002
P_B_FS	-0.8367	0.7141	1	-0.6498
	-30	-30	-30	-30
	P= .000	P= .000	P= .	P= .000
BA_ASP	0.7219	-0.5353	-0.6498	1
	-30	-30	-30	-30
	P= .000	P= .002	P= .000	P= .
DEAD_BAS	-0.4193	0.4548	-0.0443	-0.1198
	-30	-30	-30	-30
	P= .021	P= .012	P= .816	P= .528
P_B_S	-0.7426	0.6157	0.9122	-0.6943
	-30	-30	-30	-30
	P= .000	P= .000	P= .000	P= .000
BA_SP	-0.7504	0.6155	0.8966	-0.6256
	-30	-30	-30	-30
	P= .000	P= .000	P= .000	P= .000
P_A_T	0.8929	-1	-0.7138	0.5352
	-30	-30	-30	-30
	P= .000	P= .000	P= .000	P= .002

Figure 35. Correlation Analysis, Gr3 Significant Variables

	BA_SP	P_A_T	DEAD_BAS	P_B_S
P_BA_ASP	-0.7504	0.8929	-0.4193	-0.7426
	-30	-30	-30	-30
	P= .000	P= .000	P= .021	P= .000
P_F_P_S	0.6155	-1	0.4548	0.6157
	-30	-30	-30	-30
	P= .000	P= .000	P= .012	P= .000
P_B_FS	0.8966	-0.7138	-0.0443	0.9122
	-30	-30	-30	-30
	P= .000	P= .000	P= .816	P= .000
BA_ASP	-0.6256	0.5352	-0.1198	-0.6943
	-30	-30	-30	-30
	P= .000	P= .002	P= .528	P= .000
DEAD_BAS	-0.0189	-0.455	1	-0.1057
	-30	-30	-30	-30
	P= .921	P= .012	P= .	P= .578
P_B_S	0.8982	-0.6155	-0.1057	1
	-30	-30	-30	-30
	P= .000	P= .000	P= .578	P= .
BA_SP	1	-0.6153	-0.0189	0.8982
	-30	-30	-30	-30
	P= .	P= .000	P= .921	P= .000
P_A_T	-0.6153	1	-0.455	-0.6155
	-30	-30	-30	-30
	P= .000	P= .	P= .012	P= .000

Figure 36. Correlation Analysis, Gr3 Significant Variables - continued

5.14 HLRM Construction and Prediction

The initial HLRM for each group entered the significant variables in order of their ranked correlation coefficients from the correlation analysis for that group. A second regression is then run on each group, this time entering the variables based on their

significant T values from the first HLRM. The best model for each groups is then tested for its predictive capability.

Group 1:

The order of entering the significant independent variables for group 1 into the first HLRM for that group, mirrors the ranking of the variables in (section 5.11). The reordering of the variables based on the Significant T values from the first HLRM are as follows: (1) percent basal area aspen, (2) percent basal are fir + percent basal area spruce, (3) number of aspen trees, (4) percent aspen trees, (5) dead basal area, (6) basal area spruce, (7) basal area aspen. The variable "percent fir trees + percent spruce trees" drops out of the first HLRM as a insignificant variable.

To determine the best HLRM for each model, the second HLRM is monitored to determine when the adjusted R square value begins to drop off as the multiple R value continues to rise. It is at this point, that the addition of variables into the regression stops explaining any more to the variance. In the case of group 1 this occurred in the fifth step on the HLRM (see Figure 37). The resulting 4 significant variables from group1 include, in order of significance: (1) percent basal area aspen, (2) percent basal area fir + percent basal area spruce. (3) number of aspen, (4) percent aspen trees. At this point in the regression the multiple R = .76143 and the adjusted R square = .44. The model was then tested by entering the biophysical data for the 14 test stands for group 1 into the regression equation and comparing predicted value for SBE against the expected value for SBE (see Appendix G). In the case of group 1, the resulting correlation between

predicted SBE and expected SBE was .117112. This same procedure was used on group 2 and group 3, with the following results.

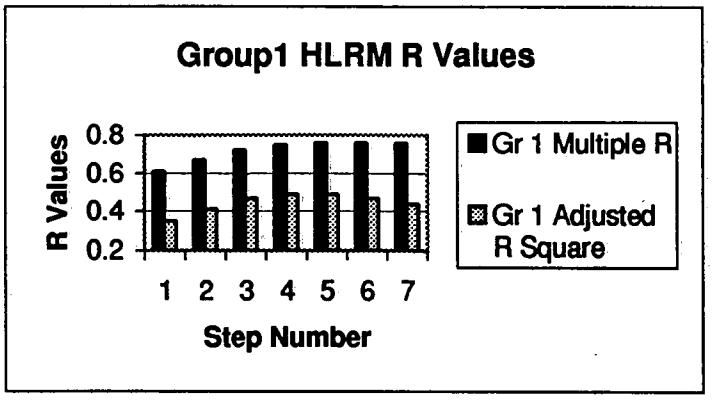

Figure 37. Group 1 HLRM R Values

Group : 2

The order of entering the significant independent variables for group 2 into the first HLRM for that group, mirrors the ranking of the variables in (section 5.12). The reordering of the variables based on the Significant T values from the first HLRM are as follows: (1) percent basal area aspen, (2) percent aspen trees, (3) basal area aspen, (4) basal area spruce, (5) percent spruce trees, (6) average basal for all trees, (7) percent basal area spruce, (8) percent basal area fir + percent basal area spruce. The variable "percent fir trees + percent spruce trees" drops out of the first HLRM as a insignificant variable.

In the case of group 2 the best HLRM occurred in the fifth step on the HLRM (see Figure 38). The resulting 4 significant variables from group 2 include, in order of significance: (1) percent basal area aspen, (2) percent aspen trees, (3) basal area aspen, (4) basal area spruce. At this point in the regression the multiple R = .75719 and the adjusted

R square = .41080. The model is then tested by entering the biophysical data for the 14 test stands for group 2 into the regression equation and comparing predicted value for SBE against the expected value for SBE (see Appendix G). In the case of group 2, the resulting correlation between predicted SBE and expected SBE was .263102.

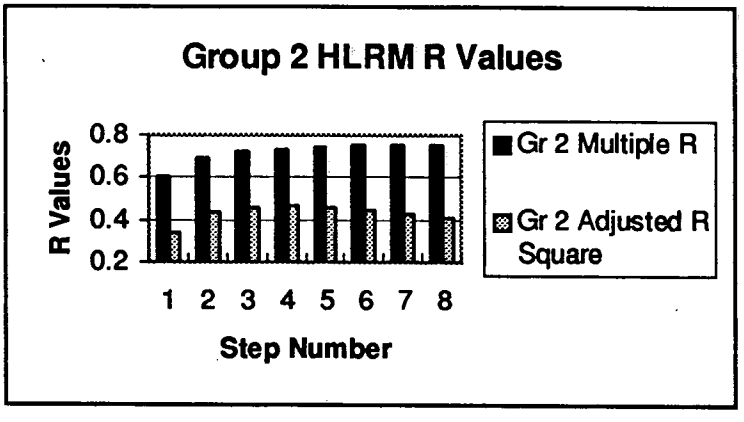

Figure 38. Group 2 HLRM R Values

Group : 3

The order of entering the significant independent variables for group 3 into the first HLRM for that group, mirrors the ranking of the variables in (section 5.13). The reordering of the variables based on the Significant T values from the first HLRM are as follows: (1) basal area spruce, (2) percent basal area aspen, (3) percent fir trees + percent spruce trees, (4) percent basal area fir + percent basal area spruce, (5) dead basal area, (6) basal area aspen, (7) percent basal area spruce. The variable "percent aspen trees" drops out of the first HLRM as a insignificant variable.

In the case of group 3 the best HLRM occurred in the fifth step on the HLRM (see Figure 39). The resulting 4 significant variables from group 3 include, in order of

significance: (1) basal area spruce, (2) percent basal area aspen, (3) percent fir trees + percent spruce trees, (4) percent basal area fir + percent basal area spruce. At this point in the regression the multiple R = .64147 and the adjusted R square = .31733. The model is then tested by entering the biophysical data for the 14 test stands for group 3 into the regression equation and comparing predicted value for SBE against the expected value for SBE (see Appendix G). In the case of group 3, the resulting correlation between predicted SBE and expected SBE was .406489. The correlation coefficients of the three groups are then compared with the correlation coefficients of the NN models.

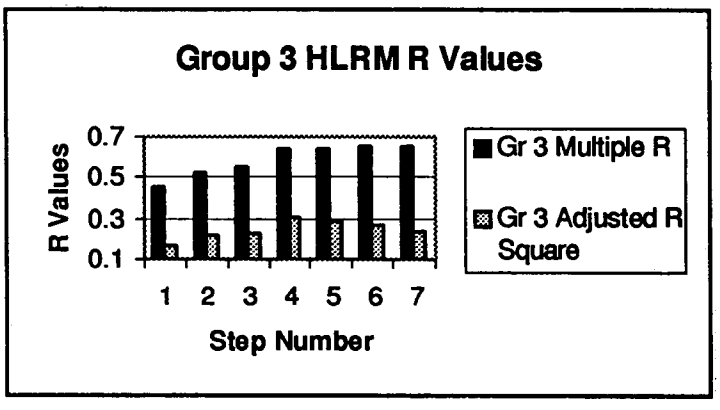

Figure 39. Group3 HLRM R Values

5.20 Neural Network Models

A number of NN models were constructed and tested to determine which architecture produced the best prediction of SBE. From the tested NN's, the best two were chosen to compare with the HLRM's. The architecture for these two NN's (Neural Network 1, NN1 and Neural Network 2, NN2), is discussed in methods section 4.31 (NN Construction and Testing). The resulting NN correlation coefficients for each group were

averaged, to produce a mean NN correlation coefficient for that group (see Appendix G). The mean correlation coefficient values for each group are as follows: Group 1 = .142, Group 2 = .344 and Group 3 = .710 with an a mean correlation coefficient across all groups of .365. The resulting NN correlation coefficient values were then compared with the correlation coefficients from the HLRM's (see Appendix G).

5.30 Comparison of Neural Networks and Regression Models

The direct comparison, via correlation analysis, of the predictive capability of NN versus the predictive capability of HLRM's in this research reveals that NN's consistently provide more accurate predictions of scenic beauty than HLRM. In the case of Group 1 the HLRM correlation coefficient was .117 and the mean NN correlation coefficient was .142 (see figure 40). In the case of Group 2 the HLRM correlation coefficient was .263 and the mean NN correlation coefficient was .334 (see Figure 41). In the case of Group 3 the HLRM correlation coefficient was .406 and the mean NN correlation coefficient was .710 (see Figure 42).

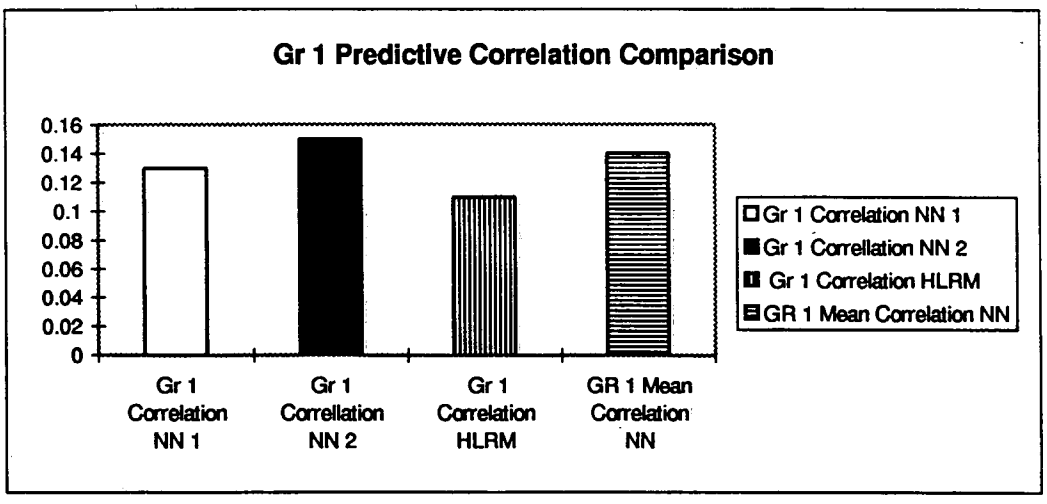

Figure 40. Group 1 Predictive Correlation Comparison

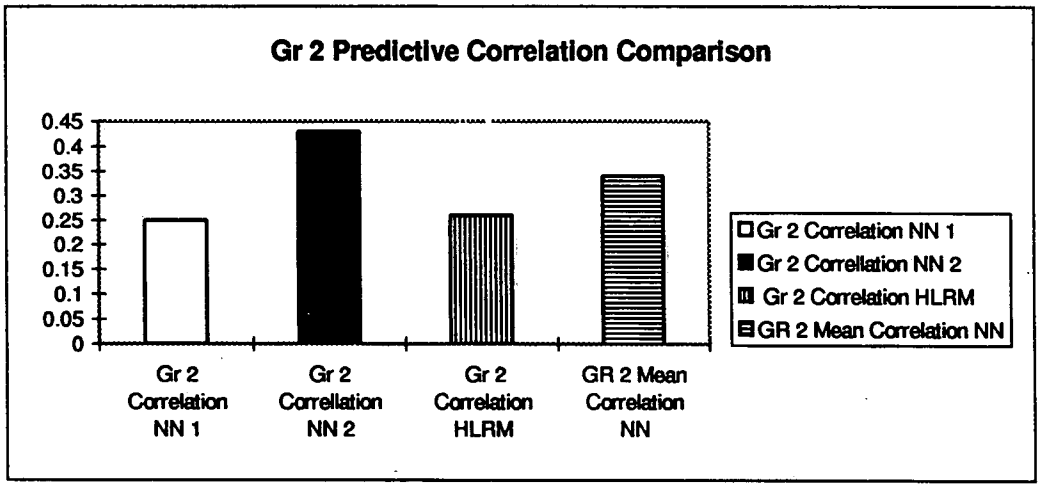

Figure 41. Group 2 Predictive Correlation Comparison

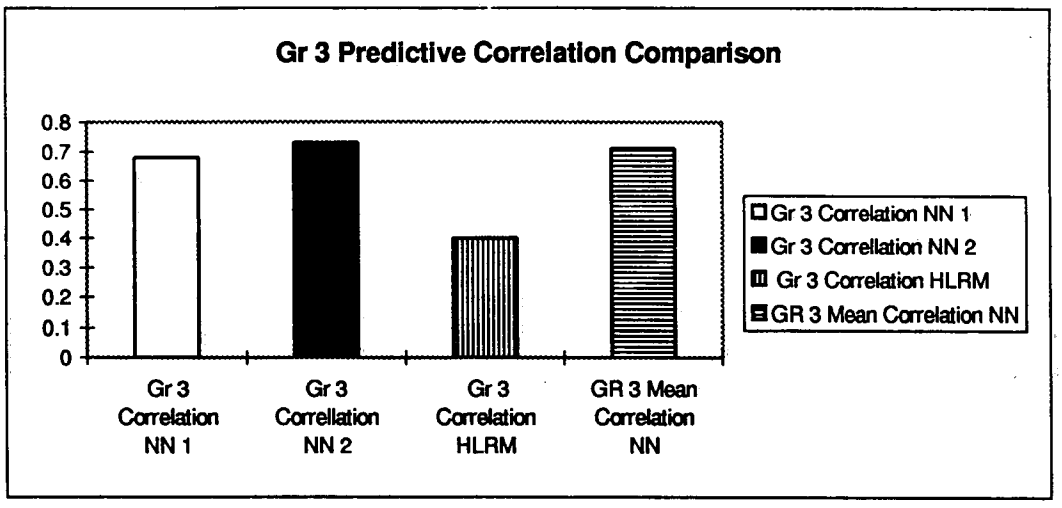

Figure 42. Group 3 Predictive Correlation Comparison

6.0 Discussion

Model Comparison:

This research illustrates that, with this particular data set, the NN models are consistently more accurate predictors of scenic beauty. In the case of the three groups the highest correlation coefficient of predicted SBE and expected SBE for the HLRM was .406 for group 3 while the NN correlation coefficient was .71. The NN also had a consistently higher correlation coefficient for the other two groups. It is interesting to note that for neither Group 1 nor Group 2 could the NN or HLRM predict SBE to any degree of accuracy. In the case of Group 3, although the HLRM showed a marked improvement in its predictive capability the NN had nearly twice the correlation coefficient for this group. The reason for this variability between groups is likely due to the random chance that Group 3 had a better distribution of differences within the stand data for the learning

group of 30 and the testing group of 14. It is evident that to construct optimal NN's and HLRM's it would be advantageous to have a larger and more diverse sample of stands.

It is also evident from the low correlation coefficient values between SBE and the biophysical variables (see figure 19), that perhaps a better method for presenting the slides to subjects exists. One method, according to Daniel (personal comment), is instead of randomizing all the slides for all the stands is to present 4 slides, as a panoramic sequence, for each photo point and to ask the subject to rate the SBE of the points. Preliminary findings of this research indicates a higher correlation exists between this method and on site rating of the same points. This may lead to better predicting models for both the NN's and the HLRM's.

7.0 Conclusions

This research investigated, summarized, and tested two methodologies for the prediction of near view scenic beauty and addressed the following research question posed by Bishop (1996). What is the predictive capability of a neural network compared with a regression model, based on the same variables? This was achieved by developing, modifying, and assessing a series of multiple linear regression models designed to predict near view scenic beauty, utilizing standard USDA Forest Service stand data and related scenic beauty estimation data. A series of neural network models that mirror the structural components of tested multiple linear regression models were constructed and the predictive capability of the linear regression model was compared with that of the neural network based on the same dependent and independent variables. It was found, in the

context of this research, that based on the same set of input variables, neural networks models were consistently, though not greatly, more capable of predicting near view scenic beauty in spruce/fir forest than hierarchical linear regression models.

7.1 Limitations of Study

The primary limitation of this research concerns the forest stand biophysical data used to construct the NN and HLRM models. The nature and purpose of the collection of this data is directly related to timber harvest activities. It a apparent from this research that this type of data may not be appropriate for the prediction of near view scenic beauty and that other data types need to be collected to construct more effective models. This topic is further addressed at the conclusion of section 7.2 (Future Research).

7.2 Future Research

This research compares the predictive capability of NN with that of HLRM's , the same set of data. The method used relies on building the HLRM's first and then constructing NN's using the significant variables indicated by the HLRM analysis. An alternative to this method is to build the HLRM's separately for the NN's. In this case the HLRM's and NN's would dictate which independent variables are most significant to their particular model. This may reveal that the NN's and HLRM's indicate different significant variables for the prediction of near view SBE. The predictive capability of the two model types could then be investigated independent of each other.

The models from this research have only been tested with regard to near view scenic beauty in spruce/fir forest types. This method, however, could also be tested in other forest types and also adapted to a vista model. The results of this near view research indicate that the NN is a somewhat better predictor of SBE, but only in the context of this study. Further research needs to be conducted to test this method under varying vegetative conditions.

The use of HLRM's as opposed to other statistical methods was dictated by the literature. It was evident early in this research, via correlation analysis of the biophysical variables with each other, that most of the independent variables had high correlation coefficients. HLRM's tend to report inflated adjusted R square values in models where the independent variables covary, and the resulting models, when tested, tend to be poor predictive models. This proved to be true in this study as evident by the high adjusted R of the HLRM for groups 1 and two, and their poor predictive capability. Group 3 had a relatively lower adjust R square value but proved to be a better predictor of SBE for both NN's and HLRM's. The fact that most of the significant variables from the biophysical data do covary indicate that this type of data may not be appropriate for predicted near view SBE.

Based on the stepwise linear regression, the variable "percent basal area aspen" fell out as the primary predictor of near view SBE for all groups including the entire sample. This positive correlation between "percent basal area aspen" and near view SBE indicates that the subjects preferred stands with a larger component of big aspens. The inclusion of other quantifiable biophysical data in the HLRM's and the NN, that don't covary with

aspen, should be researched to determine what other data should be included in these types of models.

8.0 Appendix A: Sample RMStand Output for Location 107, Site 35

SITE INDEX & PRODUCTIVITY

Species	DBH AGE	---- SITE ------ -----INDEX------ HGT	Product-ivity	BASE 100	BASE 80	BASE 50	Reference
PIEN	168	57	40	41	.0	20	Alexander, RM-32 INT-75,223
ABLA	138	62	49	51	.0	28	Alexander, RM-32 INT-75,223
PIEN	123	67	56	59	.0	35	Alexander, RM-32 INT-75,223
PIEN	89	80	79	86	.0	56	Alexander, RM-32 INT-75,223
ABLA	156	66	52	51	.0	28	Alexander, RM-32 INT-75,223
ABLA	124	57	45	50	.0	27	Alexander, RM-32 INT-75,223

PIEN - E.SPRUCE 58 62 .0 37 Average (3 TREES)

* Site Productivity is Based on Brickell, INT-75, Total Age is Estimated by adding 4 years for Hardwoods, 15 for Softwoods & 30 for Spruce

FOREST TYPE & STANDSIZE
WHITE SPRUCE MATURE

ANNUAL MORTALITY X CAUSE

MEASURE	INSECT	DISEASE	FIRE	ANIMAL	WEATHER	SUPPRESSED	OTHER
Stems(1-4.9)	.00	.00	.00	.00	.00	.00	.00
Stems(5IN+)	.00	.00	.00	.00	.00	.00	3.39
Cubic(5IN+)	.00	.00	.00	.00	.00	.00	46.75
Scrib(7IN+)	.00	.00	.00	.00	.00	.00	170.87

LIVE TREES PER ACRE X DAMAGE

DAMAGE	0-4.9IN	5-8.9IN	9IN+
1- NONE	550.0	347.7	87.1
54- FROST CR	.0	23.7	.0
74- DEAD TOP	12.5	.0	2.9

NET Cubic Volume of Growing Stock = 3610. (Min. DBH = 5.0 Min. DIB = 4.0)
NET Scrib Volume of Growing Stock = 14984. (Min. DBH = 7.0 Min. DIB = 6.0)
% Nonstocked = .0 % Nonstockable = .0
METHOD C SAMP 4 LINES 41 BAF 40 FPS 50 LFPS .0 SFPS .0 GP .0
END OF PAGE - INDIVIDUAL STAND RUN 2- 2-1997

Loc-Site 002107-0035 Reg 2 District 0702 Survey Date 9408 Acres 17 PAGE 2

TREES X SPECIES & DBH CLASS

Nonstockable Points Included in Average

DIA CLS	ALL LIVE TREES LIVE TREES	AVG DBH	AVG BA	AV HGT	AVG CR	AVG DMR	DEAD MORT. TREES	ALL LIVE TREES DIA AGE	HGT GRO	TOTAL GRO	MERCH CUBIC	MERCH SCRIB
SUBALPINE FIR												
-1	237.5	.5	.0	5	3	.0	.0	.0	.2	.0	.0	.0
1	87.5	1.5	1.1	11	4	.0	.0	.0	.0	5	.0	.0
2	37.5	2.5	1.3	11	3	.0	.0	.0	.0	6	.0	.0
3	37.5	3.5	2.5	23	4	.0	.0	.0	.0	27	.0	.0
4	25.0	4.3	2.6	23	2	.0	.0	.0	.0	27	.0	.0
5	176.2	5.6	30.0	38	3	.0	.0	84	.8	538	311	.0
6	91.0	6.3	20.0	27	3	.0	.0	.0	.0	258	160	.0
7	34.4	7.3	10.0	35	5	.0	.0	.0	.0	165	123	327
8	23.7	8.8	10.0	50	4	.0	.0	.0	.0	235	177	675
10	33.6	10.4	20.0	63	6	.0	17.0	156	.5	588	434	1682
1"+	546.3	5.7	97.4							1850	1204	2683
ENGELMANN SPRUCE												
.0	12.5	.0	20.0	1	2	.0	.0	.0	.2	.0	.0	.0
-1	75.0	.5	20.0	5	3	.0	.0	.0	.3	.0	.0	.0
1	12.5	1.5	.2	13	2	.0	.0	.0	.0	1	.0	.0
2	37.5	2.5	1.3	15	4	.0	.0	.0	.0	10	.0	.0
6	46.2	6.3	10.0	37	4	.0	.0	73	.5	196	113	.0
11	12.9	11.9	10.0	55	3	.0	.0	.0	.0	270	220	1034
12	11.0	12.9	10.0	60	4	.0	.0	.0	.0	290	245	1036
14	17.1	14.6	20.0	62	5	.0	.0	145	.6	583	453	2089
17	5.8	17.8	10.0	70	6	.0	.0	.0	.0	312	254	1360
23	3.3	23.5	10.0	80	6	.0	.0	187	.9	324	270	1559
25	2.9	25.2	10.0	100	7	.0	.0	.0	.0	392	331	2041
29	2.1	29.8	10.0	90	8	.0	.0	.0	.0	326	274	1728
38	1.3	38.1	10.0	96	7	.0	.0	.0	.0	297	246	1454
1"+	152.6	11.0	101.4							3000	2406	12301
STAND TOTAL												
1"+	698.9	7.2	198.8							4851	3610	14984

GROWTH & MORTALITY / ACRE

	INGROWTH	ACCRETION	GROSS-GROWTH	MORTALITY	NET
CUBIC	18.6	51.4	70.0	46.7	23.2
SCRIBNER	32.7	224.4	257.1	170.9	86.2

Based on 6 tallied growth trees out of 34 live growing stock trees

NET Cubic Volume of Growing Stock = 3610. (Min. DBH = 5.0 Min. DIB = 4.0)

NET Scrib Volume of Growing Stock = 14984. (Min. DBH = 7.0 Min. DIB = 6.0)

% Nonstocked = .0 % Nonstockable = .0

METHOD C SAMP 4 LINES 41 BAF 40 FPS 50 LFPS .0 SFPS .0 GP .0

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ALL LIVE TREES

DIA CLS	LIVE TREES	AVG DBH	BASAL AREA	AVG HGT	GROWING STOCK	SOUND CULL	ROTTEN CULL	% SOFTWD	TOT CU.	MERC CU.	MERC SCRIB
.0	325.0	.5	.4	5	325.0	.0	.0	100	.0	.0	.0
2	175.0	1.9	3.6	12	175.0	.0	.0	100	23	.0	.0
4	62.5	3.8	5.0	23	62.5	.0	.0	100	55	.0	.0
6	313.3	5.9	59.7	35	313.3	.0	.0	100	992	584	.0
8	58.1	7.9	19.8	41	58.1	.0	.0	100	400	300	1002
10	33.6	10.4	20.0	63	33.6	.0	.0	100	588	434	1682
12	24.0	12.4	20.0	57	24.0	.0	.0	100	560	465	2070
14	17.1	14.6	20.0	62	17.1	.0	.0	100	583	453	2089
16	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
18	5.8	17.8	10.0	70	5.8	.0	.0	100	312	254	1360
20	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
22	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
24	3.3	23.5	10.0	80	3.3	.0	.0	100	324	270	1559
26	2.9	25.2	10.0	100	2.9	.0	.0	100	392	331	2041
28	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
30	3.3	33.0	19.7	92	3.3	.0	.0	100	622	520	3182
1"+	698.9	7.2	197.8		698.9	.0	.0	100	4851	3610	14984

ALL DEAD TREES

DIA CLS	DEAD TREES	AVG DBH	AVG BA	AVG HGT	SALV. DEAD	DEAD MORT.	NONSOUND DEAD	% SOFTWD	TOTAL CU.	MERCH CU.	MERCH SCRIB
.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
2	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
4	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
6	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
8	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
10	17.0	10.4	10.0	60	.0	17.0	.0	100	280	234	854
12	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
14	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
16	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
18	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
20	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
22	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
24	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
26	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
28	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
30	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
1"+	17.0	10.4	10.0		.0	17.0	.0	100	280	234	854

STAND TOTAL

1"+ 715.9 7.3 207.8 698.9 17.0 .0 100 5131 3844 15838

NET Cubic Volume of Growing Stock = 3610. (Min. DBH = 5.0 Min. DIB = 4.0)

NET Scrib Volume of Growing Stock = 14984. (Min. DBH = 7.0 Min. DIB = 6.0)

% Nonstocked = .0 % Nonstockable = .0

METHOD C SAMP 4 LINES 41 BAF 40 FPS 50 LFPS .0 SFPS .0 GP .0

END OF PAGE - INDIVIDUAL STAND RUN 2- 2-1997

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PER ACRE POINT SUMMARY OF STEMS & BA

POINT#	LIVE TREES 0-5	5-9	9-12	12-99	ALL	BASAL AREA LIVE SWD	LIVE	SWD	MISTLETOE TREES	DMR
1	1000.0	858.	52.	78.	1988.	1988.	294.	294.	.0	.0
2	650.0	533.	70.	34.	1288.	1288.	208.	208.	.0	.0
3	.0	0.	0.	38.	38.	38.	160.	160.	.0	.0
4	600.0	95.	64.	23.	782.	782.	133.	133.	.0	.0

STATISTICAL SUMMARIES OF TOTALS

	TREES	BASAL AREA	CUBIC	SCRIBNER
L Growing Stock	1024.	199.	3610.	14984.
C Sound Cull	0.	0.	0.	0.
R Rotten Cull	0.	0.	0.	0.
M Mort Standing	17.	10.	234.	854.
F Mort Down	0.	0.	0.	0.
S SND D. Stand.	0.	0.	0.	0.
G SND Dead Down	0.	0.	0.	0.
D Nonsound Dead	0.	0.	0.	0.
TOTAL	1041.	209.	3844.	15838.
CV% (Total)	78.	29.	15.	50.
SE% (Total)	34.	13.	6.	22.
70%CI (Total)	446.	33.	306.	4363.

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% Nonstocked = .0 % Nonstockable = .0
METHOD C SAMP 4 LINES 41 BAF 40 FPS 50 LFPS .0 SFPS .0 GP .0
END OF PAGE - INDIVIDUAL STAND RUN 2- 2-1997

Loc-Site 002107-0035 Reg 2 District 0702 Survey Date 9408 Acres 17 PAGE 5
RMRIS DATA

TIM PRODUCTIVITY:	58	SITE INDEX PIEN	62
TREE SURVEY METHOD:	C	BF SW:	14984
TREE SURVEY DATE:	9408	CUBIC SAW SW:	2726
FOREST TYPE:	WS	CUBIC SAW HW:	.0
STAND SIZE CLASS:	9	CUBIC POLE SW:	884
PCT NON STOCKED:	.0	CUBIC POLE HW:	.0
ORIGIN DATE:	1812	CUBIC CULL/WOODLAND:	.0
QMD X 10:	72 (87-5+)	CUBIC SOUND DEAD:	234
STAND HEIGHT:	41	PCT DOWN SOUND DEAD:	.0
BASAL AREA 1"+	199 (190-5+)	HARD (SOUND) SNAGS:	.0
TOTAL TREES 0"+:	1024 (699-1+)	SOFT(ROTTEN) SNAGS:	.0
LARGE TREES 5"+:	461	GROSS CUBIC GROWTH:	70
CONE SEROTINY:	.0	CUBIC MORTALITY:	47
FREQUENT DAMAGE:	74 (DEAD TOP)		
MISTLETOE (DMR):	.0	BEETLE RISK:	3

LIVE TREE BASAL & TREES X SPECIES & DBH

	FIR	SPR	PP	OP	JP	DF	AS	OH	OS	FIR	SPR	PP	OP	JP	DF	AS	OH	OS
DBH		BAA									TREES							
0	.0	.0	.0	.0	.0	.0	.0	.0	.0	238	88	.0	.0	.0	.0	.0	.0	.0
1-4	7	1	.0	.0	.0	.0	.0	.0	.0	188	50	.0	.0	.0	.0	.0	.0	.0
5-8	70	10	.0	.0	.0	.0	.0	.0	.0	325	46	.0	.0	.0	.0	.0	.0	.0
9-15	20	40	.0	.0	.0	.0	.0	.0	.0	34	41	.0	.0	.0	.0	.0	.0	.0
16-20	.0	10	.0	.0	.0	.0	.0	.0	.0	.0	6	.0	.0	.0	.0	.0	.0	.0
21+	.0	40	.0	.0	.0	.0	.0	.0	.0	.0	10	.0	.0	.0	.0	.0	.0	.0
1+	97	101	.0	.0	.0	.0	.0	.0	.0	546	153	.0	.0	.0	.0	.0	.0	.0

SDI	AGE	MAI	PAI	AMD	100%	40%	60%	%AMD	STRUCTURE	STAGE	ELK
415	182	20	23	305		122	183	65%	4C	Mature	MB

WRITE IN DIAGNOSIS - Stand Condition

Habitat Type: Growth Comment: Density:
Structure: Composition: Condition:
Arrangment: Fuel Loading Other:

NET Cubic Volume of Growing Stock = 3610. (Min. DBH = 5.0 Min. DIB = 4.0)
NET Scrib Volume of Growing Stock = 14984. (Min. DBH = 7.0 Min. DIB = 6.0)
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METHOD C SAMP 4 LINES 41 BAF 40 FPS 50 LFPS .0 SFPS .0 GP .0
END OF PAGE - INDIVIDUAL STAND RUN 2- 2-1997

9.0 Appendix B: Normalized Explicit and Implicit Biophysical Data

Parcel	Stand	No_fir	AvDbh_Fir	No_Sp	AvDbh_Sp	No_F/S	No_Asp	AvDbh_Asp
105	14	0.10136	0.033	0.4148	0.083	0.14284	0.0489	0.1
105	17	0.04713	0.031	0.4071	0.06	0.08784	0.0563	0.121
105	18	0.0348	0.058	0.1981	0.084	0.05461	0.1111	0.064
105	25	0.02376	0.058	0.0651	0.056	0.03027	0.1509	0.114
105	40	0.09853	0.042	0.0749	0.051	0.10602	0.1791	0.099
105	45	0.05653	0.034	0.0408	0.122	0.06061	0.0206	0.154
106	6	0.02577	0.081	0.0699	0.062	0.03276	0.0123	0.172
106	7	0.00712	0.06	0.0563	0.13	0.01275	0.0194	0.123
106	11	0.0327	0.054	0.035	0.044	0.0362	0.3209	0.063
106	18	0.00828	0.072	0.0823	0.096	0.01651	0.1554	0.097
106	33	0.0032	0.087	0.1813	0.096	0.02133	0	0
106	34	0.01582	0.04	0.0354	0.166	0.01936	0	0
106	37	0.04087	0.053	0.0615	0.149	0.04702	0.2427	0.073
107	12	0.00801	0.096	0.1167	0.121	0.01968	0	0
107	13	0.00417	0.117	0.1451	0.116	0.01868	0.051	0.08
107	14	0.0117	0.052	0.3456	0.069	0.04626	0	0
107	17	0.02762	0.078	0.1615	0.119	0.04377	0	0
107	21	0.01432	0.104	0.1738	0.1	0.0317	0.0191	0.139
107	23	0.00583	0.133	0.0053	0.236	0.00636	0.1511	0.093
107	35	0.05463	0.057	0.1526	0.11	0.06989	0	0
108	14	0.00576	0.095	0.0644	0.135	0.0122	0.0765	0.098
108	16	0.03866	0.056	0.0031	0.217	0.03897	0.1601	0.091
108	17	0.0009	0.135	0.1225	0.132	0.01315	0	0
111	49	0.00293	0.112	0.0766	0.145	0.01059	0	0
114	1	0.00509	0.108	0	0	0.00509	0.3231	0.085
114	4	0.03022	0.043	0.1747	0.089	0.04769	0.0486	0.113
114	8	0.06262	0.038	0.2312	0.074	0.08574	0.3954	0.053
114	11	0.00069	0.087	0.3161	0.051	0.0323	0.0297	0.098
114	12	0.03916	0.036	0.1687	0.102	0.05603	0.0364	0.108
114	20	0.0373	0.036	0.176	0.067	0.0549	0.1063	0.074
114	23	0.02648	0.032	0.3929	0.044	0.06577	0.2346	0.083
114	24	0.06359	0.032	0.1138	0.103	0.07497	0.0287	0.12
114	25	0.09767	0.029	0.0699	0.118	0.10466	0.0414	0.109
114	26	0.06672	0.028	0.2375	0.063	0.09047	0.1762	0.089
114	28	0.08345	0.034	0.2637	0.068	0.10982	0.1904	0.092
114	55	0.01224	0.064	0.0471	0.13	0.01695	0.0685	0.096
114	69	0.03232	0.039	0.0635	0.129	0.03867	0.0169	0.11
118	102	0.05849	0.044	0.0892	0.056	0.06741	0.2413	0.087
123	42	0.0795	0.021	0.5175	0.058	0.13125	0.0607	0.131
124	14	0.03044	0.071	0.0743	0.131	0.03787	0.0382	0.12
125	25	0	0	0	0	0	0.8118	0.023
125	56	0.00849	0.08	0.0064	0.138	0.00913	0.0469	0.102
126	2	0.01	0.017	0.0641	0.197	0.01641	0	0
126	19	0.03958	0.032	0.0683	0.147	0.04641	0.0257	0.154

No_Tot_Tr	AvDbh_Tot	Live_Basal	Ave Basel Per All Trees	Dead_Basal	Tot_Basal	Per_Fir_Tr
0.14773	0.055	0.2403	0.016266161	0	0.2403	0.686116564
0.09346	0.054	0.1504	0.016092446	0.0149	0.1654	0.504279906
0.06572	0.068	0.1644	0.025015216	0.0497	0.2141	0.529519172
0.04536	0.081	0.1608	0.035449735	0.0133	0.1741	0.523809524
0.12392	0.054	0.1975	0.015937702	0.055	0.2525	0.795109748
0.06267	0.053	0.0953	0.015206638	0.06	0.1553	0.902026488
0.034	0.083	0.1274	0.037470588	0.04	0.1674	0.757941176
0.01469	0.101	0.0821	0.055888359	0.052	0.1341	0.484683458
0.0683	0.058	0.1235	0.018081991	0.0315	0.1551	0.478770132
0.03204	0.091	0.1446	0.045131086	0.024	0.1686	0.258426966
0.02134	0.095	0.1043	0.048875351	0.06	0.1643	0.14995314
0.01936	0.08	0.067	0.034607438	0.05	0.117	0.81714876
0.07129	0.073	0.2078	0.029148548	0.025	0.2328	0.573292187
0.01968	0.111	0.1332	0.067682927	0.0267	0.1599	0.407012195
0.02378	0.109	0.1553	0.065306981	0.0133	0.1686	0.175357443
0.04626	0.065	0.105	0.022697795	0.0108	0.1157	0.252918288
0.04376	0.095	0.2167	0.04952011	0.0285	0.2452	0.631170018
0.03361	0.104	0.1983	0.059000298	0.04	0.2383	0.426063672
0.02148	0.111	0.1438	0.066945996	0.032	0.1758	0.27141527
0.06989	0.072	0.1978	0.028301617	0.01	0.2078	0.781656889
0.01985	0.111	0.1327	0.066851385	0.0186	0.1513	0.290176322
0.05498	0.07	0.1464	0.026627865	0.04	0.1864	0.703164787
0.01314	0.132	0.1251	0.095205479	0.0089	0.134	0.068493151
0.01059	0.137	0.1079	0.101888574	0.03	0.1379	0.27667611
0.0374	0.089	0.1601	0.042807487	0	0.1601	0.136096257
0.05255	0.07	0.1406	0.026755471	0.0544	0.195	0.575071361
0.12529	0.051	0.1777	0.014183095	0.06	0.2377	0.499800463
0.03527	0.058	0.0636	0.018032322	0.0107	0.0743	0.019563368
0.05967	0.067	0.1454	0.024367354	0.0482	0.1935	0.656276186
0.06553	0.053	0.0999	0.015244926	0.0292	0.129	0.569204944
0.08922	0.054	0.1436	0.016095046	0.012	0.1556	0.296794441
0.07784	0.054	0.1239	0.015917266	0.0325	0.1564	0.816932169
0.1088	0.046	0.1255	0.011534926	0.0533	0.1788	0.897702206
0.10809	0.051	0.1552	0.014358405	0.0455	0.2008	0.617263392
0.12886	0.054	0.2058	0.015970821	0.1	0.3058	0.647602049
0.0238	0.09	0.1042	0.043781513	0.0115	0.1157	0.514285714
0.04037	0.066	0.0955	0.02365618	0.0556	0.1511	0.800594501
0.09154	0.06	0.1762	0.019248416	0.0171	0.1934	0.638955648
0.13733	0.048	0.1685	0.012269715	0.0067	0.1752	0.578897546
0.04169	0.09	0.1831	0.043919405	0.07	0.2531	0.730151115
0.08118	0.023	0.0233	0.002870165	0	0.0233	0
0.01382	0.092	0.0632	0.045730825	0.0066	0.0698	0.614327062
0.01641	0.124	0.1375	0.083790372	0.024	0.1615	0.609384522
0.04898	0.071	0.136	0.027766435	0	0.136	0.808084933

Per_Sp_Tr	Per_Flr_Tr+Pers_Spr_Tr	Per_Asp_Tr	Ba_Flr	Pers_Ba_Flr	Ba_Sp
0.280782509	0.966899073	0.033100927	0.596	0.248023304	0.1549
0.435587417	0.939867323	0.060239675	0.245	0.148125756	0.0812
0.30143031	0.830949483	0.169050517	0.634	0.296123307	0.0766
0.143518519	0.667328042	0.332671958	0.433	0.248707639	0.011
0.060442221	0.855551969	0.144528728	0.93	0.368316832	0.0108
0.06510292	0.967129408	0.032870592	0.359	0.231165486	0.0333
0.205588235	0.963529412	0.036176471	0.933	0.55734767	0.0144
0.383253914	0.867937372	0.132062628	0.141	0.105145414	0.052
0.05124451	0.530014641	0.469838946	0.518	0.333978079	0.0036
0.256866417	0.515293383	0.485018727	0.236	0.139976275	0.0414
0.849578257	0.999531396	0	0.133	0.080949483	0.0912
0.18285124	1	0	0.141	0.120512821	0.0533
0.086267359	0.659559546	0.340440454	0.633	0.271907216	0.075
0.592987805	1	0	0.4	0.250156348	0.0933
0.610176619	0.785534062	0.214465938	0.311	0.184460261	0.1066
0.747081712	1	0	0.171	0.147796024	0.0885
0.369058501	1.000228519	0	0.914	0.372756933	0.1257
0.517108004	0.943171675	0.056828325	0.844	0.354175409	0.0942
0.024674115	0.296089385	0.703445065	0.56	0.3185438	0.016
0.218343111	1	0	0.974	0.468719923	0.1014
0.324433249	0.614609572	0.385390428	0.286	0.18902842	0.0643
0.005638414	0.708803201	0.291196799	0.669	0.358905579	0.008
0.932267884	1.000761035	0	0.089	0.06641791	0.1663
0.72332389	1	0	0.2	0.145032632	0.088
0	0.136096257	0.863903743	0.324	0.202373517	0
0.33244529	0.907516651	0.092483349	0.311	0.159487179	0.0761
0.184531886	0.684332349	0.315587836	0.494	0.207824989	0.0694
0.89622909	0.915792458	0.084207542	0.029	0.039030956	0.0454
0.282721636	0.938997821	0.061002179	0.272	0.140568475	0.0959
0.268579277	0.837784221	0.162215779	0.259	0.200775194	0.0429
0.440372114	0.737166555	0.262945528	0.151	0.097043702	0.0409
0.146197328	0.963129496	0.036870504	0.353	0.225703325	0.0662
0.064246324	0.961948529	0.038051471	0.458	0.256152125	0.0533
0.219724304	0.836987695	0.163012305	0.279	0.138944223	0.0512
0.204640695	0.852242744	0.147757256	0.54	0.176586004	0.0656
0.19789916	0.712184874	0.287815126	0.27	0.233362143	0.0432
0.157295021	0.957889522	0.041862769	0.269	0.178027796	0.0579
0.09744374	0.736399388	0.263600612	0.624	0.322647363	0.0153
0.376829535	0.955727081	0.044200102	0.195	0.11130137	0.0937
0.178220197	0.908371312	0.091628688	0.831	0.328328724	0.07
0	0	1	0	0	0
0.046309696	0.660636758	0.339363242	0.3	0.429799427	0.0067
0.390615478	1	0	0.017	0.010526316	0.136
0.139444671	0.947529604	0.052470396	0.227	0.166911765	0.0804

Pers_Ba_Sp	Pers_Ba_Flr/Spr	Ave_Ba_Per_F/S	Ba_Asp	Pers_Ba_Asp
0.644610903	0.892634207	0.015016802	0.0267	0.111111111
0.490931076	0.639056832	0.012033242	0.045	0.272067715
0.35777674	0.653900047	0.02563633	0.025	0.116767865
0.063182079	0.311889719	0.017938553	0.1067	0.612866169
0.042772277	0.411089109	0.009790606	0.095	0.376237624
0.214423696	0.445589182	0.011417258	0.0267	0.171925306
0.086021505	0.643369176	0.032875458	0.02	0.119474313
0.387770321	0.492915735	0.051843137	0.016	0.119313945
0.023210832	0.35718891	0.015303867	0.0686	0.442295293
0.245551601	0.385527877	0.039370079	0.08	0.474495848
0.555082167	0.636031649	0.04899203	0	0
0.455555556	0.576068376	0.03481405	0	0
0.322164948	0.594072165	0.029413016	0.07	0.300687285
0.583489681	0.833646029	0.06773374	0	0
0.632265718	0.816725979	0.073715203	0.0178	0.105575326
0.764909248	0.912705272	0.022827497	0	0
0.512642741	0.885399674	0.049600183	0	0
0.395300042	0.749475451	0.056340694	0.02	0.083927822
0.091012514	0.409556314	0.113207547	0.072	0.409556314
0.487969201	0.956689124	0.028444699	0	0
0.424983477	0.614011897	0.076147541	0.04	0.264375413
0.042918455	0.401824034	0.019219913	0.072	0.386266094
1.241044776	1.307462687	0.133231939	0	0
0.638143582	0.783176215	0.101983003	0	0
0	0.202373517	0.063654224	0.1279	0.798875703
0.39025641	0.54974359	0.022478507	0.0338	0.173333333
0.291964661	0.499789651	0.013855843	0.0602	0.253260412
0.611036339	0.650067295	0.01495356	0.0157	0.211305518
0.495607235	0.636175711	0.021970373	0.023	0.118863049
0.33255814	0.533333333	0.012531876	0.0317	0.245736434
0.26285347	0.359897172	0.00851452	0.088	0.565552699
0.423273657	0.648976982	0.013538749	0.0225	0.143861893
0.298098434	0.554250559	0.009468756	0.0267	0.149328859
0.25498008	0.393924303	0.00874323	0.0768	0.38247012
0.214519294	0.391105298	0.010890548	0.0872	0.285153695
0.37337943	0.606741573	0.041415929	0.0343	0.296456353
0.38318994	0.561217737	0.021929144	0.0111	0.073461284
0.079110651	0.401758014	0.01152648	0.0996	0.514994829
0.534817352	0.646118721	0.008624762	0.0567	0.323630137
0.276570525	0.604899249	0.040427779	0.03	0.118530225
0	0	0	0.0233	1
0.095988539	0.525787966	0.040197152	0.0267	0.38252149
0.842105263	0.852631579	0.083912249	0	0
0.591176471	0.758088235	0.02221504	0.0333	0.244852941

Ave_Ba_Per_Asp	Lg_Tr_Gt5	SBE Normal
0.054601227	0.527	0.156214063
0.079928952	0.297	0.20110625
0.02250225	0.395	0.118135484
0.070709079	0.254	0.272268485
0.053042993	0.377	0.072369375
0.12961165	0.127	0.205536129
0.162601626	0.29	0.10610125
0.082474227	0.087	0.154182188
0.021377376	0.258	0.147442813
0.051480051	0.2	0.135363438
0	0.138	0.064742581
0	0.044	0.15920129
0.028842192	0.413	0.161787
0	0.197	0.068848438
0.034901961	0.238	0.000418125
0	0.163	0.091927813
0	0.438	0.097556563
0.104712042	0.161	0.125787188
0	0.215	0.110958438
0	0.461	0.13593125
0.052287582	0.199	0.229203182
0.044971893	0.19	0.184359333
0	0.098	0.213964783
0	0.106	0.1148225
0	0.354	0.24830303
0.069547325	0.233	0.134751563
0.015225089	0.278	0.10932875
0.052861953	0.096	0.12533375
0.063186813	0.217	0.093036875
0.029821261	0.189	0.115476563
0.037510656	0.332	0.222650313
0.078397213	0.178	0.075917188
0.064492754	0.221	0.124777813
0.043586833	0.267	0.176715806
0.045798319	0.389	0.176394375
0.050072993	0.195	0.2815955
0.065680473	0.137	0.130112581
0.041276419	0.33	0.297833077
0.093410214	0.165	0.232504615
0.078534031	0.267	0.1505435
0.002870165	0.001	0.18824
0.056929638	0.138	0.186188846
0	0.064	0.027107813
0.129571984	0.09	0.146568378

10.0 Appendix C: Stepwise LRM: All Biophysical Variables All Data

**** MULTIPLE REGRESSION ****

Listwise Deletion of Missing Data
Equation Number 1 Dependent Variable.. SBE_NORM SBE Normal
Block Number 1. Method: Stepwise Criteria PIN .0500 POUT .1000
A_B_P_AS, A_B_PFS, AVDBH_AS, AVDBH_FI, AVDBH_SP, AVDBH_TO,
AVE_BASE, BA_ASP, BA_FIR, BA_SP, DEAD_BAS, LG_TR_GT, LIVE_BAS,
NO_ASP, NO_F_S, NO_FIR, NO_SP, NO_TOT_T, P_A_T, P_B_F,
P_B_FS, P_B_S, P_BA_ASP, P_F_P_S, P_F_T, PER_SP_T, TOT_BASA

Variable(s) Entered on Step Number
1.. P_BA_ASP Pers_Ba_Asp

Multiple R .55465
R Square .30763
Adjusted R Square .29115
Standard Error .05466

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	1	.05575	.05575
Residual	42	.12546	.00299

F = 18.66143 Signif F = .0001

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.161412	.037365	.554646	4.320	.0001
(Constant)	.110289	.012234		9.015	.0000

**** MULTIPLE REGRESSION ****

Equation Number 1 Dependent Variable.. SBE_NORM SBE Normal

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
A_B_P_AS	.171767	.206411	.999827	1.351	.1842
A_B_PFS	-.011605	-.013244	.901676	-.085	.9328
AVDBH_AS	.145127	.169280	.941999	1.100	.2778
AVDBH_FI	.001066	.001255	.959698	.008	.9936
AVDBH_SP	.024197	.025619	.776126	.164	.8705
AVDBH_TO	.031061	.034080	.833505	.218	.8282
AVE_BASE	.003058	.003405	.858544	.022	.9827
BA_ASP	.214961	.168279	.424303	1.093	.2807
BA_FIR	-.026408	-.031546	.988013	-.202	.8408
BA_SP	.058425	.049511	.497220	.317	.7525
DEAD_BAS	-.116287	-.132991	.905564	-.859	.3952
LG_TR_GT	.046636	.055978	.997562	.359	.7214
LIVE_BAS	.038795	.046366	.988959	.297	.7678
NO_ASP	-.541618	-.365611	.315492	-2.515	.0159
NO_F_S	.089185	.106949	.995647	.689	.4949
NO_FIR	.067533	.081159	.999954	.521	.6049
NO_SP	.097423	.115376	.971052	.744	.4613
NO_TOT_T	.016908	.019602	.930626	.126	.9007
P_A_T	-.521241	-.316990	.256065	-2.140	.0383
P_B_F	.030220	.036231	.995145	.232	.8176
P_B_FS	.287790	.197498	.326072	1.290	.2043
P_B_S	.136223	.116939	.510216	.754	.4552
P_F_P_S	.521694	.317333	.256174	2.143	.0381
P_F_T	.144422	.166755	.923052	1.083	.2852
PER_SP_T	-.009187	-.009358	.718379	-.060	.9525
TOT_BASA	-.012520	-.014675	.951216	-.094	.9256

**** MULTIPLE REGRESSION ****

Equation Number 1 Dependent Variable.. SBE_NORM SBE Normal

Variable(s) Entered on Step Number
2.. NO_ASP

Multiple R	.63260
R Square	.40018
Adjusted R Square	.37092
Standard Error	.05149

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	2	.07252	.03626
Residual	41	.10869	.00265

F = 13.67705 Signif F = .0000

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
NO_ASP	-2.36863E-04	9.4173E-05	-.541618	-2.515	.0159
P_BA_ASP	.291820	.062668	1.002754	4.657	.0000
(Constant)	.104008	.011793		8.820	.0000

**** MULTIPLE REGRESSION ****

Equation Number 1 Dependent Variable.. SBE_NORM SBE Normal

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
A_B_P_AS	.051234	.059818	.258009	.379	.7067
A_B_PFS	-.042286	-.051614	.311874	-.327	.7455
AVDBH_AS	-.009934	-.010872	.227659	-.069	.9455
AVDBH_FI	-.070808	-.087363	.300170	-.555	.5822
AVDBH_SP	-.034043	-.038187	.306805	-.242	.8103
AVDBH_TO	-.054713	-.062492	.296188	-.396	.6942
AVE_BASE	-.047587	-.056280	.308304	-.357	.7233
BA_ASP	.078969	.063207	.165086	.401	.6909
BA_FIR	-.008253	-.010573	.311637	-.067	.9470
BA_SP	.150917	.134619	.202751	.859	.3953
DEAD_BAS	-.039882	-.047490	.272412	-.301	.7652
LG_TR_GT	.055663	.071753	.315218	.455	.6516
LIVE_BAS	.039365	.050546	.314327	.320	.7506
NO_F_S	.100365	.129223	.314075	.824	.4147
NO_FIR	.084659	.109140	.314522	.694	.4914
NO_SP	.089427	.113744	.313708	.724	.4732
NO_TOT_T	.107546	.129218	.293553	.824	.4147
P_A_T	-.352553	-.215423	.209669	-1.395	.1707
P_B_F	-.012744	-.016254	.309303	-.103	.9186
P_B_FS	.244166	.179370	.203918	1.153	.2557
P_B_S	.150026	.138296	.236663	.883	.3824
P_F_P_S	.353142	.215833	.209722	1.398	.1698
P_F_T	.095519	.116921	.307172	.745	.4609
PER_SP_T	-.014915	-.016321	.283054	-.103	.9183
TOT_BASA	.020214	.025317	.301601	.160	.8736

End Block Number 1 PIN = .050 Limits reached.

11.0 Appendix D: Best HLRM Group 1

```
Block Number  1.  Method:  Enter      P_BA_ASP


Variable(s) Entered on Step Number
   1..     P_BA_ASP


Multiple R            .61209
R Square              .37465
Adjusted R Square     .35232
Standard Error        .05602

Analysis of Variance
                          DF   Sum of Squares      Mean Square
Regression                1        .05265           .05265
Residual                  28       .08787           .00314

F =       16.77490        Signif F =  .0003

------------------ Variables in the Equation ------------------

Variable                B         SE B       Beta          T  Sig T

P_BA_ASP          .172102      .042020    .612086      4.096  .0003
(Constant)        .104862      .015657                 6.697  .0000


------------- Variables not in the Equation -------------

Variable     Beta In  Partial  Min Toler         T  Sig T

P_B_FS       .515531  .355349    .297114     1.975  .0585
NO_ASP      -.578139 -.363215    .246823    -2.026  .0528
P_A_T       -.505611 -.309012    .233583    -1.688  .1029
DEAD_BAS    -.185771 -.218533    .865370    -1.164  .2547
BA_SP        .156908  .134506    .459532      .705  .4866
BA_ASP       .266228  .233749    .482075     1.249  .2223


End Block Number   1   All requested variables entered.
```

Block Number 2. Method: Enter P_B_FS

Variable(s) Entered on Step Number
2.. P_B_FS

Multiple R	.67351
R Square	.45361
Adjusted R Square	.41314
Standard Error	.05333

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	2	.06374	.03187
Residual	27	.07678	.00284

F = 11.20782 Signif F = .0003

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.293629	.073380	1.044299	4.001	.0004
P_B_FS	.145525	.073670	.515531	1.975	.0585
(Constant)	-.011714	.060868		-.192	.8488

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
NO_ASP	-.561193	-.377006	.159843	-2.076	.0480
P_A_T	-.510455	-.333744	.149403	-1.805	.0826
DEAD_BAS	.122967	.097500	.102823	.500	.6216
BA_SP	-.154077	-.111825	.186083	-.574	.5710
BA_ASP	.352236	.325254	.252847	1.754	.0912

End Block Number 2 All requested variables entered.

Block Number 3. Method: Enter NO_ASP

Variable(s) Entered on Step Number
3.. NO_ASP

Multiple R	.72889
R Square	.53127
Adjusted R Square	.47719
Standard Error	.05033

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	3	.07465	.02488
Residual	26	.06587	.00253

F = 9.82317 Signif F = .0002

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.426844	.094428	1.518080	4.520	.0001
P_B_FS	.141062	.069567	.499721	2.028	.0530
NO_ASP	-2.42540E-04	1.1686E-04	-.561193	-2.076	.0480
(Constant)	-.018865	.057553		-.328	.7457

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
P_A_T	-.382145	-.259641	.121046	-1.344	.1909
DEAD_BAS	.284940	.233430	.061791	1.200	.2413
BA_SP	.081481	.057791	.137819	.289	.7746
BA_ASP	.197795	.170910	.102763	.867	.3940

End Block Number 3 All requested variables entered.

Block Number 4. Method: Enter P_A_T

Variable(s) Entered on Step Number
4.. P_A_T

Multiple R	.75025
R Square	.56287
Adjusted R Square	.49293
Standard Error	.04957

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	4	.07909	.01977
Residual	25	.06143	.00246

F = 8.04789 Signif F = .0003

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.497619	.106864	1.769795	4.657	.0001
P_B_FS	.142656	.068522	.505367	2.082	.0477
NO_ASP	-1.98932E-04	1.1957E-04	-.460292	-1.664	.1087
P_A_T	-.102821	.076486	-.382145	-1.344	.1909
(Constant)	-.023347	.056778		-.411	.6844

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
DEAD_BAS	.234516	.195540	.059149	.977	.3384
BA_SP	.022404	.016234	.112754	.080	.9373
BA_ASP	.143160	.125478	.076490	.620	.5414

End Block Number 4 All requested variables entered.

Block Number 5. Method: Enter DEAD_BAS

Variable(s) Entered on Step Number
5.. DEAD_BAS

Multiple R	.76131
R Square	.57959
Adjusted R Square	.49200
Standard Error	.04961

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	5	.08144	.01629
Residual	24	.05908	.00246

F = 6.61733 Signif F = .0005

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.604500	.153015	2.149919	3.951	.0006
P_B_FS	.229535	.112315	.813141	2.044	.0521
NO_ASP	-2.39590E-04	1.2671E-04	-.554366	-1.891	.0708
P_A_T	-.088806	.077889	-.330057	-1.140	.2655
DEAD_BAS	7.02011E-04	7.1868E-04	.234516	.977	.3384
(Constant)	-.121795	.115704		-1.053	.3030

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
BA_SP	-.029375	-.021318	.058963	-.102	.9194
BA_ASP	.001321	.000909	.022294	.004	.9966

End Block Number 5 All requested variables entered.

Block Number 6. Method: Enter BA_SP

Variable(s) Entered on Step Number
6.. BA_SP

Multiple R	.76143
R Square	.57978
Adjusted R Square	.47015
Standard Error	.05067

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	6	.08147	.01358
Residual	23	.05905	.00257

F = 5.28882 Signif F = .0015

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.603603	.156516	2.146730	3.856	.0008
P_B_FS	.237746	.140013	.842227	1.698	.1030
NO_ASP	-2.34021E-04	1.4040E-04	-.541481	-1.667	.1091
P_A_T	-.089864	.080216	-.333990	-1.120	.2742
DEAD_BAS	7.16380E-04	7.4730E-04	.239316	.959	.3477
BA_SP	-4.80801E-05	4.7018E-04	-.029375	-.102	.9194
(Constant)	-.124275	.120629		-1.030	.3136

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
BA_ASP	.002904	.001996	.022170	.009	.9926

End Block Number 6 All requested variables entered.

Block Number 7. Method: Enter BA_ASP

Variable(s) Entered on Step Number
7.. BA_ASP

Multiple R	.76143
R Square	.57978
Adjusted R Square	.44607
Standard Error	.05181

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	7	.08147	.01164
Residual	22	.05905	.00268

F = 4.33620 Signif F = .0037

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.601673	.260987	2.139864	2.305	.0310
P_B_FS	.237267	.152008	.840532	1.561	.1328
NO_ASP	-2.32881E-04	1.8825E-04	-.538843	-1.237	.2291
P_A_T	-.089785	.082445	-.333699	-1.089	.2879
DEAD_BAS	7.10616E-04	9.8122E-04	.237390	.724	.4766
BA_SP	-4.83093E-05	4.8137E-04	-.029515	-.100	.9210
BA_ASP	5.29069E-06	5.6505E-04	.002904	.009	.9926
(Constant)	-.123654	.139998		-.883	.3866

End Block Number 7 All requested variables entered.

12.0 Appendix E: Best HLRM Group 2

Listwise Deletion of Missing Data

Equation Number 1 Dependent Variable.. SBE_NORM

Block Number 1. Method: Enter P_BA_ASP

Variable(s) Entered on Step Number
1.. P_BA_ASP

Multiple R	.60772
R Square	.36932
Adjusted R Square	.34680
Standard Error	.05701

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	1	.05329	.05329
Residual	28	.09100	.00325

F = 16.39659 Signif F = .0004

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.178221	.044013	.607718	4.049	.0004
(Constant)	.104035	.015094		6.893	.0000

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
P_A_T	-.682583	-.417821	.236307	-2.390	.0241
BA_ASP	.366516	.328224	.505782	1.806	.0822
BA_SP	-.165909	-.153178	.537605	-.805	.4276
PER_SP_T	-.183459	-.195803	.718408	-1.038	.3087
AVE_BASE	-.155183	-.181418	.861947	-.959	.3463
P_B_S	-.165910	-.144275	.476921	-.758	.4553
P_B_FS	-.083437	-.053275	.257121	-.277	.7837

End Block Number 1 All requested variables entered.

Block Number 2. Method: Enter P_A_T

Variable(s) Entered on Step Number
2.. P_A_T

Multiple R	.69240
R Square	.47942
Adjusted R Square	.44086
Standard Error	.05275

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	2	.06918	.03459
Residual	27	.07512	.00278

F = 12.43267 Signif F = .0001

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.353153	.083768	1.204224	4.216	.0002
P_A_T	-.184474	.077197	-.682583	-2.390	.0241
(Constant)	.097747	.014211		6.878	.0000

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
BA_ASP	.291063	.282079	.165978	1.499	.1459
BA_SP	-.221636	-.223698	.210332	-1.170	.2525
PER_SP_T	-.212372	-.248851	.223151	-1.310	.2016
AVE_BASE	.055350	.059792	.144463	.305	.7625
P_B_S	-.231038	-.219327	.203604	-1.146	.2621
P_B_FS	-.115571	-.081126	.146257	-.415	.6815

Block Number 3. Method: Enter BA_ASP

Variable(s) Entered on Step Number
3.. BA_ASP

Multiple R	.72169
R Square	.52084
Adjusted R Square	.46556
Standard Error	.05157

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	3	.07515	.02505
Residual	26	.06914	.00266

F = 9.42064 Signif F = .0002

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.273230	.097720	.931693	2.796	.0096
P_A_T	-.163472	.076762	-.604872	-2.130	.0428
BA_ASP	6.05718E-04	4.0403E-04	.291063	1.499	.1459
(Constant)	.091019	.014600		6.234	.0000

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
BA_SP	-.212726	-.223673	.154164	-1.147	.2621
PER_SP_T	-.170818	-.204356	.164476	-1.044	.3066
AVE_BASE	.051893	.058425	.113968	.293	.7722
P_B_S	-.155821	-.147059	.160753	-.743	.4642
P_B_FS	-.064256	-.046612	.122956	-.233	.8174

End Block Number 3 All requested variables entered.

Block Number 4. Method: Enter BA_SP

Variable(s) Entered on Step Number
4.. BA_SP

Multiple R	.73812
R Square	.54481
Adjusted R Square	.47199
Standard Error	.05126

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	4	.07861	.01965
Residual	25	.06568	.00263

F = 7.48067 Signif F = .0004

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.242377	.100783	.826487	2.405	.0239
P_A_T	-.174096	.076859	-.644184	-2.265	.0324
BA_ASP	5.90645E-04	4.0180E-04	.283820	1.470	.1540
BA_SP	-3.81832E-04	3.3277E-04	-.212726	-1.147	.2621
(Constant)	.124331	.032457		3.831	.0008

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
PER_SP_T	-.125501	-.146719	.154144	-.727	.4745
AVE_BASE	.081876	.093612	.111423	.461	.6492
P_B_S	.074956	.045339	.153693	.222	.8259
P_B_FS	.180830	.108625	.122228	.535	.5974

End Block Number 4 All requested variables entered.

Block Number 5. Method: Enter PER_SP_T

Variable(s) Entered on Step Number
5.. PER_SP_T

Multiple R	.74472
R Square	.55461
Adjusted R Square	.46182
Standard Error	.05175

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	5	.08003	.01601
Residual	24	.06427	.00268

F = 5.97715 Signif F = .0010

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.241537	.101755	.823622	2.374	.0260
P_A_T	-.178334	.077814	-.659864	-2.292	.0310
BA_ASP	5.30129E-04	4.1411E-04	.254740	1.280	.2127
BA_SP	-3.03735E-04	3.5273E-04	-.169216	-.861	.3977
PER_SP_T	-.033999	.046789	-.125501	-.727	.4745
(Constant)	.133174	.034954		3.810	.0009

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
AVE_BASE	.130261	.144043	.108968	.698	.4921
P_B_S	.284616	.147354	.119383	.714	.4821
P_B_FS	.237981	.141705	.121434	.687	.4992

End Block Number 5 All requested variables entered.

Block Number 6. Method: Enter AVE_BASE

Variable(s) Entered on Step Number
6.. AVE_BASE

Multiple R	.75090
R Square	.56385
Adjusted R Square	.45008
Standard Error	.05231

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	6	.08136	.01356
Residual	23	.06293	.00274

F = 4.95578 Signif F = .0022

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.287771	.122337	.981275	2.352	.0276
P_A_T	-.217250	.096410	-.803860	-2.253	.0341
BA_ASP	5.06830E-04	4.1994E-04	.243544	1.207	.2397
BA_SP	-3.16349E-04	3.5702E-04	-.176244	-.886	.3847
PER_SP_T	-.044044	.049438	-.162580	-.891	.3822
AVE_BASE	.036939	.052914	.130261	.698	.4921
(Constant)	.121198	.039279		3.086	.0052

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
P_B_S	.255293	.132629	.107269	.628	.5367
P_B_FS	.187304	.108734	.099712	.513	.6130

End Block Number 6 All requested variables entered.

Block Number 7. Method: Enter P_B_S

Variable(s) Entered on Step Number
7.. P_B_S

Multiple R	.75599
R Square	.57153
Adjusted R Square	.43519
Standard Error	.05301

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	7	.08247	.01178
Residual	22	.06183	.00281

F = 4.19215 Signif F = .0045

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.277977	.124960	.947878	2.225	.0367
P_A_T	-.206399	.099224	-.763710	-2.080	.0494
BA_ASP	6.19162E-04	4.6168E-04	.297523	1.341	.1936
BA_SP	-5.92423E-04	5.6956E-04	-.330050	-1.040	.3096
PER_SP_T	-.061995	.057691	-.228844	-1.075	.2942
AVE_BASE	.032932	.054004	.116131	.610	.5482
P_B_S	.076198	.121407	.255293	.628	.5367
(Constant)	.112459	.042171		2.667	.0141

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
P_B_FS	.119444	.065057	.094077	.299	.7681

End Block Number 7 All requested variables entered.

Block Number 8. Method: Enter P_B_FS

Variable(s) Entered on Step Number
8.. P_B_FS

Multiple R	.75719
R Square	.57334
Adjusted R Square	.41080
Standard Error	.05414

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	8	.08273	.01034
Residual	21	.06156	.00293

F = 3.52744 Signif F = .0097

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
P_BA_ASP	.292255	.136284	.996566	2.144	.0439
P_A_T	-.203814	.101712	-.754143	-2.004	.0582
BA_ASP	6.14814E-04	4.7177E-04	.295433	1.303	.2066
BA_SP	-6.17541E-04	5.8777E-04	-.344044	-1.051	.3054
PER_SP_T	-.060505	.059135	-.223342	-1.023	.3179
AVE_BASE	.028904	.056782	.101927	.509	.6160
P_B_S	.061549	.133343	.206214	.462	.6491
P_B_FS	.040260	.134757	.119444	.299	.7681
(Constant)	.093140	.077695		1.199	.2440

End Block Number 8 All requested variables entered.

13.0 Appendix F: Optimal HLRM Group 3

Listwise Deletion of Missing Data

Equation Number 1 Dependent Variable.. SBE_NORM

Block Number 1. Method: Enter BA_SP

Variable(s) Entered on Step Number
1.. BA_SP

Multiple R .45109
R Square .20348
Adjusted R Square .17503
Standard Error .06329

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	1	.02865	.02865
Residual	28	.11216	.00401

F = 7.15295 Signif F = .0124

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
BA_SP	-6.82162E-04	2.5506E-04	-.451089	-2.675	.0124
(Constant)	.199709	.019165		10.420	.0000

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
P_BA_ASP	.416752	.308630	.436835	1.686	.1033
P_F_P_S	-.158898	-.140316	.621118	-.736	.4678
P_B_FS	.240988	.119566	.196074	.626	.5367
DEAD_BAS	-.370817	-.415417	.999643	-2.373	.0250
BA_ASP	.292743	.255890	.608597	1.375	.1803
P_B_S	.254169	.125204	.193281	.656	.5175

End Block Number 1 All requested variables entered.

Block Number 2. Method: Enter P_BA_ASP

Variable(s) Entered on Step Number
2.. P_BA_ASP

Multiple R	.52854
R Square	.27935
Adjusted R Square	.22597
Standard Error	.06131

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	2	.03934	.01967
Residual	27	.10148	.00376

F = 5.23313 Signif F = .0120

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
BA_SP	-2.09206E-04	3.7381E-04	-.138340	-.560	.5803
P_BA_ASP	.118041	.070013	.416752	1.686	.1033
(Constant)	.138255	.040905		3.380	.0022

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
P_F_P_S	.412814	.215278	.137834	1.124	.2713
P_B_FS	.858139	.370906	.134628	2.037	.0520
DEAD_BAS	-.333676	-.296636	.248881	-1.584	.1253
BA_ASP	.157683	.126354	.332142	.649	.5217
P_B_S	.425685	.214232	.177748	1.118	.2736

End Block Number 2 All requested variables entered.

Block Number 3. Method: Enter P_F_P_S

Variable(s) Entered on Step Number
3.. P_F_P_S

Multiple R	.55924
R Square	.31275
Adjusted R Square	.23345
Standard Error	.06101

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	3	.04404	.01468
Residual	26	.09678	.00372

F = 3.94397 Signif F = .0192

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
BA_SP	-1.31300E-04	3.7840E-04	-.086824	-.347	.7314
P_BA_ASP	.233391	.124037	.824002	1.882	.0711
P_F_P_S	.118947	.105819	.412814	1.124	.2713
(Constant)	.009483	.121577		.078	.9384

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
P_B_FS	.856411	.379044	.120713	2.048	.0512
DEAD_BAS	-.366805	-.331650	.119264	-1.758	.0910
BA_ASP	.077896	.060377	.099443	.302	.7648
P_B_S	.436690	.224976	.134510	1.154	.2592

End Block Number 3 All requested variables entered.

Block Number 5. Method: Enter DEAD_BAS

Variable(s) Entered on Step Number
5.. DEAD_BAS

Multiple R	.64644
R Square	.41789
Adjusted R Square	.29662
Standard Error	.05844

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	5	.05885	.01177
Residual	24	.08197	.00342

F = 3.44585 Signif F = .0173

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
BA_SP	-8.99459E-04	5.3915E-04	-.594779	-1.668	.1083
P_BA_ASP	.268396	.166437	.947589	1.613	.1199
P_F_P_S	.126841	.102742	.440211	1.235	.2289
P_B_FS	.182357	.165218	.648041	1.104	.2807
DEAD_BAS	-5.21499E-04	.001015	-.147628	-.514	.6122
(Constant)	-.047825	.168454		-.284	.7789

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
BA_ASP	.115646	.092645	.047939	.446	.6596
P_B_S	.031644	.014819	.064517	.071	.9439

End Block Number 5 All requested variables entered.

Block Number 4. Method: Enter P_B_FS

Variable(s) Entered on Step Number
4.. P_B_FS

Multiple R	.64147
R Square	.41149
Adjusted R Square	.31733
Standard Error	.05757

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	4	.05794	.01449
Residual	25	.08287	.00331

F = 4.37004 Signif F = .0081

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
BA_SP	-9.28478E-04	5.2823E-04	-.613968	-1.758	.0910
P_BA_ASP	.323675	.125080	1.142752	2.588	.0159
P_F_P_S	.118233	.099862	.410336	1.184	.2476
P_B_FS	.240992	.117669	.856411	2.048	.0512
(Constant)	-.103352	.127275		-.812	.4244

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
DEAD_BAS	-.147628	-.104277	.070244	-.514	.6122
BA_ASP	.066376	.055581	.089546	.273	.7874
P_B_S	.075804	.036095	.098480	.177	.8610

End Block Number 4 All requested variables entered.

Block Number 7. Method: Enter P_B_S

Variable(s) Entered on Step Number
7.. P_B_S

Multiple R .65149
R Square .42444
Adjusted R Square .24131
Standard Error .06070

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	7	.05977	.00854
Residual	22	.08105	.00368

F = 2.31767 Signif F = .0623

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
BA_SP	-9.32470E-04	6.3133E-04	-.616608	-1.477	.1539
P_BA_ASP	.210504	.210863	.743196	.998	.3290
P_F_P_S	.109324	.112395	.379416	.973	.3413
P_B_FS	.146852	.190402	.521864	.771	.4488
DEAD_BAS	-6.44077E-04	.001114	-.182327	-.578	.5689
BA_ASP	2.69028E-04	5.4291E-04	.140587	.496	.6251
P_B_S	.029695	.121776	.118346	.244	.8096
(Constant)	-.014668	.187647		-.078	.9384

End Block Number 7 All requested variables entered.

Block Number 6. Method: Enter BA_ASP

Variable(s) Entered on Step Number
6.. BA_ASP

Multiple R	.65030
R Square	.42289
Adjusted R Square	.27233
Standard Error	.05944

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	6	.05955	.00992
Residual	23	.08127	.00353

F = 2.80891 Signif F = .0336

---------- Variables in the Equation ----------

Variable	B	SE B	Beta	T	Sig T
BA_SP	-8.64142E-04	5.5406E-04	-.571426	-1.560	.1325
P_BA_ASP	.216870	.204917	.765673	1.058	.3009
P_F_P_S	.112499	.109331	.390436	1.029	.3142
P_B_FS	.164255	.172873	.583710	.950	.3519
DEAD_BAS	-6.70525E-04	.001085	-.189814	-.618	.5428
BA_ASP	2.21300E-04	4.9594E-04	.115646	.446	.6596
(Constant)	-.019431	.182772		-.106	.9163

---------- Variables not in the Equation ----------

Variable	Beta In	Partial	Min Toler	T	Sig T
P_B_S	.118346	.051919	.047204	.244	.8096

End Block Number 6 All requested variables entered.

14.0 Appendix G: NN and HLRM Prediction Comparison

Gr1 NN_1	Corr NN 1	Gr1 NN 2	Corr NN 2	Gr1 LR	Corr LR	Mean Corr NN	SBE Norm
0.146146	0.1303440	0.152049	0.1542643	0.1461523	**0.1171118**	**0.1423042**	0.1562140
0.175027		0.181117		0.2080283			0.2011062
0.104366		0.112674		0.132402			0.1181354
0.087018		0.101615		0.1264239			0.2055361
0.163135		0.164212		0.2621935			0.1474428
0.051302		0.054886		0.0588326			0.1592012
0.132273		0.137464		0.1336292			0.0004181
0.10662		0.11356		0.1232289			0.1257871
0.105024		0.105644		0.1131304			0.1359312
0.157861		0.163412		0.1711485			0.2292031
0.076218		0.078672		0.0883777			0.1148225
0.118846		0.124992		0.2189089			0.1093287
0.139353		0.147756		0.1791430			0.1154765
0.095954		0.105501		0.1199827			0.1505435

Gr 2 NN1	Corr NN 1	Gr 2 NN 2	Corr NN 2	Gr2 LR	Corr LR	Mean Corr NN	SBE Norm
0.186245	0.2509458	0.176402	0.4388951	0.1753607	**0.2631023**	**0.3449204**	0.2011062
0.251242		0.297833		0.2737804			0.2722684
0.228948		0.20797		0.2423479			0.0723693
0.12352		0.117772		0.1198534			0.1541821
0.19537		0.181942		0.1863418			0.1353634
0.16376		0.1439		0.1506491			0.161787
0.072336		0.094973		0.0763347			0.0975565
0.076739		0.097088		0.0856132			0.1359312
0.208499		0.186306		0.2067286			0.1843593
0.065719		0.091556		0.0608323			0.2139647
0.145715		0.138244		0.1411484			0.1347515
0.120649		0.123323		0.1194875			0.0930368
0.170961		0.154287		0.1579935			0.1154765
0.125747		0.122058		0.1280989			0.1505435

Gr3 NN_1	Corr NN 1	Gr 3 NN 2	Corr NN 2	Gr3 LR	Corr.LR	Mean Corr NN	SBE Norm
0.17774	0.6823448	0.172623	0.7376725	0.1744480	**0.4064885**	**0.7100086**	0.2011062
0.146839		0.137517		0.1909165			0.1061012
0.090357		0.091367		0.0834269			0.0647425
0.115341		0.110299		0.1291560			0.0688484
0.127359		0.118982		0.1526653			0.0919278
0.106965		0.128841		0.1480628			0.1109584
0.130045		0.121289		0.1512877			0.1359312
0.157021		0.154116		0.1639378			0.1154765
0.1417		0.136536		0.1520192			0.0759171
0.139798		0.144674		0.1230534			0.1763943
0.106996		0.106329		0.1151698			0.1301125
0.191878		0.187242		0.1831085			0.2325046
0.120323		0.120033		0.1231951			0.1505435
0.186579		0.177455		0.1959736			0.1465683

15.0 Appendix H: Predictor Variables Correlation Comparison

Group 1:	P_BA_ASP	P_B_FS	NO_ASP	P_A_T	SBE_NORM
P_BA_ASP	1	-0.8384	0.8679	0.8755	0.6121
	-30	-30	-30	-30	-30
	P= .	P= .000	P= .000	P= .000	P= .000
P_B_FS	-0.8384	1	-0.736	-0.7318	-0.36
	-30	-30	-30	-30	-30
	P= .000	P= .	P= .000	P= .000	P= .051
NO_ASP	0.8679	-0.736	1	0.8248	0.3885
	-30	-30	-30	-30	-30
	P= .000	P= .000	P= .	P= .000	P= .034
P_A_T	0.8755	-0.7318	0.8248	1	0.4178
	-30	-30	-30	-30	-30
	P= .000	P= .000	P= .000	P= .	P= .022
SBE_NORM	0.6121	-0.36	0.3885	0.4178	1
	-30	-30	-30	-30	-30
	P= .000	P= .051	P= .034	P= .022	P= .

Group 2:	P_BA_ASP	P_A_T	BA_ASP	BA_SP	SBE_NORM
P_BA_ASP	1	0.8739	0.703	-0.68	0.6077
	-30	-30	-30	-30	-30
	P= .	P= .000	P= .000	P= .000	P= .000
P_A_T	0.8739	1	0.5513	-0.6358	0.3698
	-30	-30	-30	-30	-30
	P= .000	P= .	P= .002	P= .000	P= .044
BA_ASP	0.703	0.5513	1	-0.4836	0.6126
	-30	-30	-30	-30	-30
	P= .000	P= .002	P= .	P= .007	P= .000
BA_SP	-0.68	-0.6358	-0.4836	1	-0.5024
	-30	-30	-30	-30	-30
	P= .000	P= .000	P= .007	P= .	P= .005
SBE_NORM	0.6077	0.3698	0.6126	-0.5024	1
	-30	-30	-30	-30	-30
	P= .000	P= .044	P= .000	P= .005	P= .

Group 3:	BA_SP	P_BA_ASP	P_F_P_S	P_B_FS	SBE_NORM
BA_SP	1	-0.7504	0.6155	0.8966	-0.4511
	-30	-30	-30	-30	-30
	P= .	P= .000	P= .000	P= .000	P= .012
P_BA_ASP	-0.7504	1	-0.8929	-0.8367	0.5206
	-30	-30	-30	-30	-30
	P= .000	P= .	P= .000	P= .000	P= .003
P_F_P_S	0.6155	-0.8929	1	0.7141	-0.3764
	-30	-30	-30	-30	-30
	P= .000	P= .000	P= .	P= .000	P= .040
P_B_FS	0.8966	-0.8367	0.7141	1	-0.3572
	-30	-30	-30	-30	-30
	P= .000	P= .000	P= .000	P= .	P= .053
SBE_NORM	-0.4511	0.5206	-0.3764	-0.3572	1
	-30	-30	-30	-30	-30
	P= .012	P= .003	P= .040	P= .053	P= .

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